

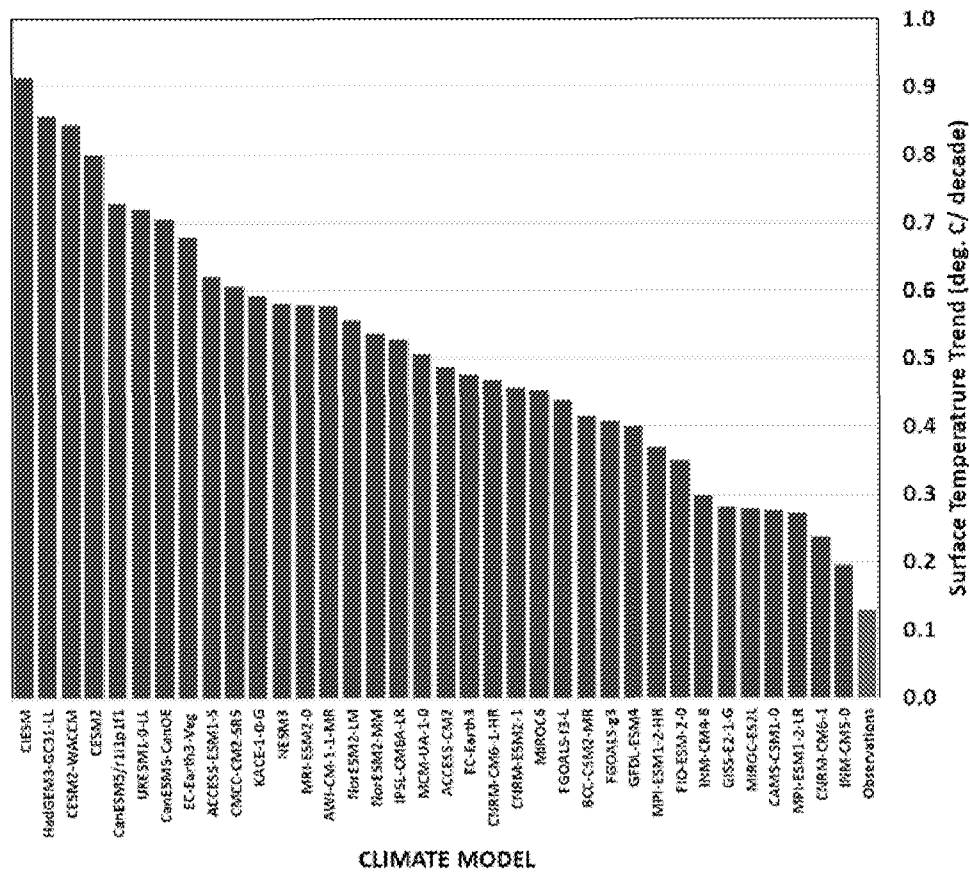


Figure 5.10: Modeled versus observed warming trends in the U.S. Corn Belt, 1973-2022.

As discussed in Chapter 9, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (*e.g.*, Seager *et al.*, 2018).

The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases might be sufficiently large that the models are simply not fit for purpose. As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from small scale processes, we believe that **the current generation of models is not fit for purpose**. (Palmer and Stevens 2019)

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the U.S. Corn Belt.

- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in W/m^2 is three times larger than the direct anthropogenic forcing of CO_2 .
- The IPCC has acknowledged some of these issues but not others.

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6 EXTREME WEATHER

Chapter Summary

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the U.S. since the 1950s, a point emphasized by AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability, but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but the trends do not persist over long periods and at the regional scale. Wildfires are not more common in the U.S. than they were in the 1980s. Burned area increased from the 1960s to the early 2000's, however it is low compared to the estimated natural baseline level. U.S. wildfire activity is strongly affected by forest management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., AR6 Seneviratne *et al.* 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. Further, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution to human-caused warming does not necessarily follow.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of Long-Term Persistence (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2016). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records that are short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

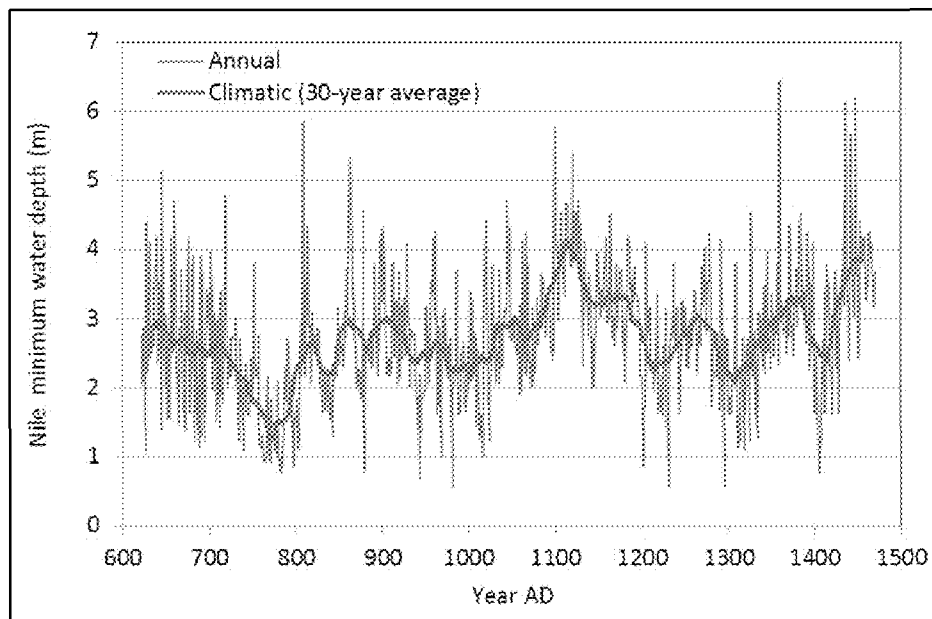


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from Koutsoyiannis (2013)

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. The Nile River is fed by precipitation over a 4 million square mile drainage basin, an area equal to about one third of CONUS. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A recurring theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA4: The U.S. Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I.

NCA5: The U.S. Climate Science Special Report of the Fifth National Climate Assessment (2023) Volume I.

In the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

Additionally we present updated data series from standard government sources to provide up-to-date information through 2024 wherever possible.

6.2 Hurricanes and tropical cyclones

AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021 p. 1585)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2023 SPM p. 9)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC 2021 p. 1585)

Since 1980, when satellite observations first fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.2.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability, a weak decrease in the number of hurricanes, and a slight but insignificant increase in the number of major hurricanes. These two trends combine to create an overall increase in the proportion of major hurricanes.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (Colorado State University, 2025). Data in the Atlantic basin extends further back than in the other ocean basins and is most relevant to U.S. policy makers.

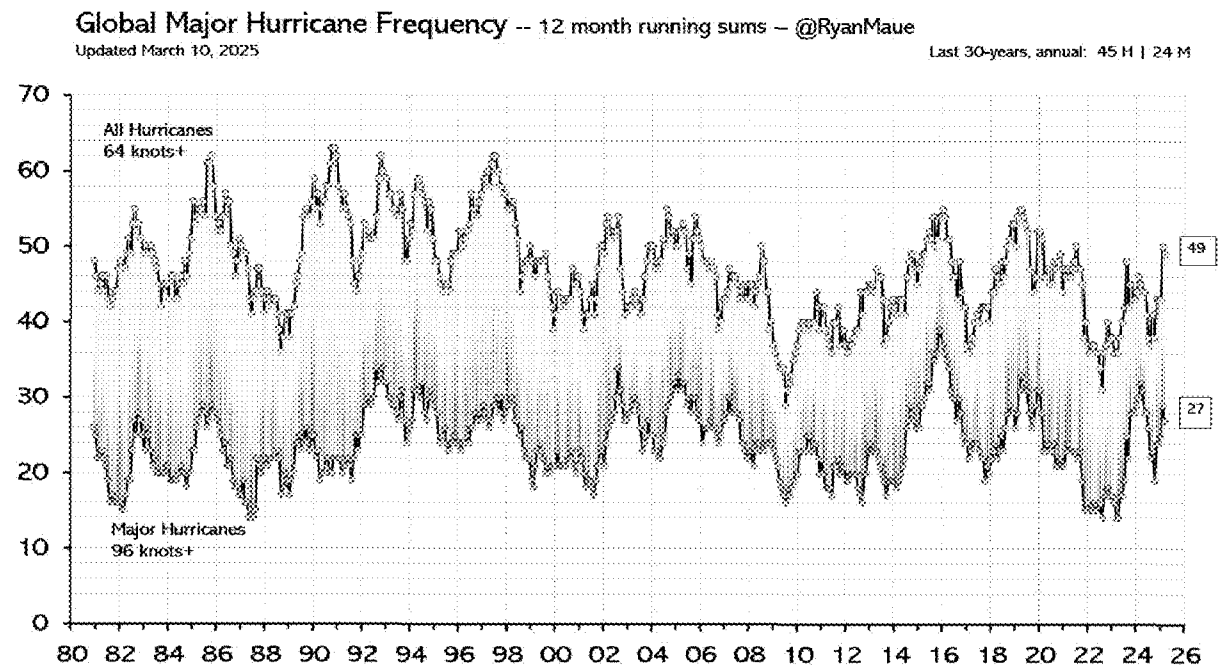


Figure 6.2.1: Global frequency of hurricanes and major hurricanes since 1980.

Figure 6.2.2 shows the frequency of Atlantic hurricanes and major hurricanes (Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (Vecchi and Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 saw exceptionally low activity, with high activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

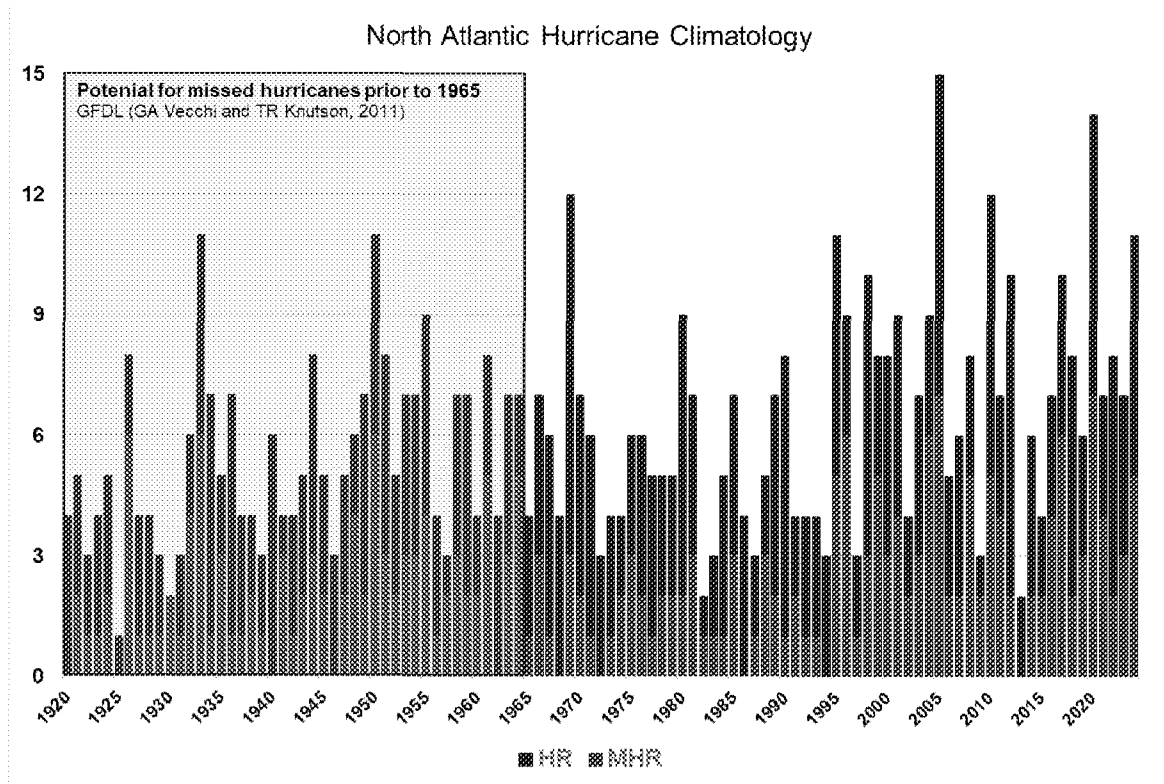


Figure 6.2.2: Atlantic frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source National Hurricane Center (2024)

Figure 6.2.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. It has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg *et al.* (2001) as associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach *et al.*, 2018).

Klotzbach *et al.* (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.2.3 updates their analysis through 2024. While the largest numbers of landfalling hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920. Figure 6.2.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, following 2005 there were no major hurricanes striking the U.S through 2016, the longest such period since 1920.

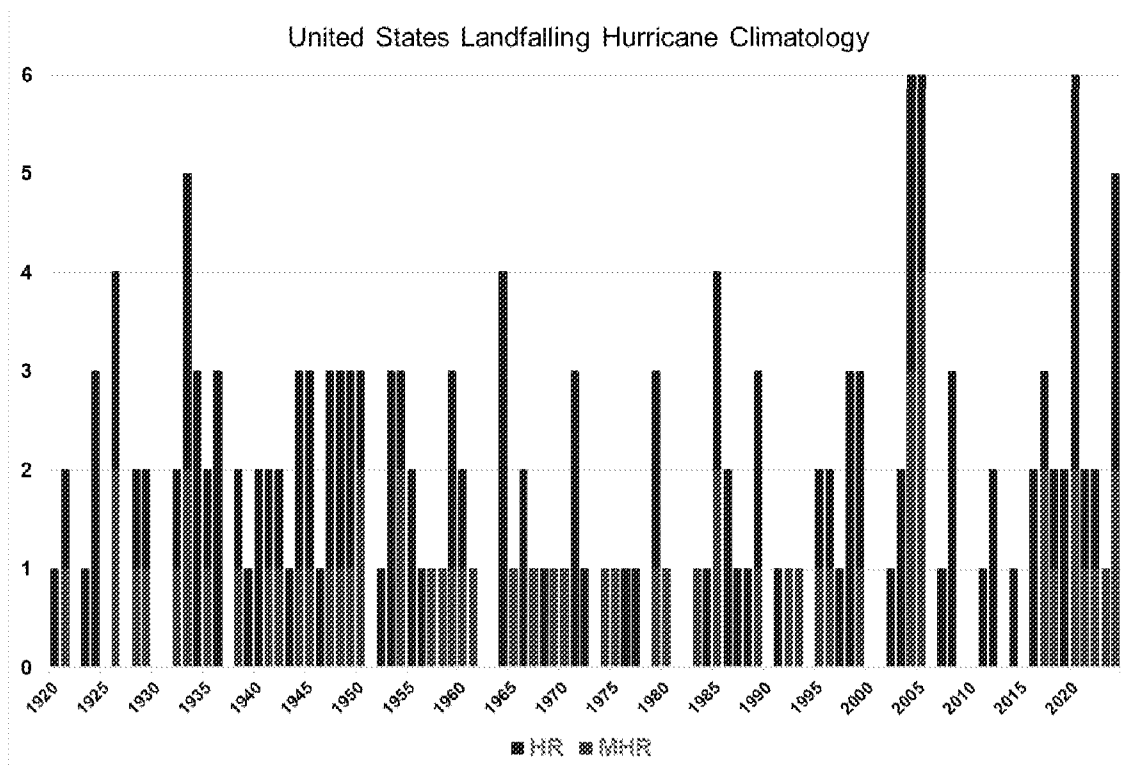


Figure 6.2.3: U.S. landfalling frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source NOAA HRD(a) (2024)

Figure 6.2.3 shows substantial interannual to multidecadal variability in U.S. landfall activity. Klotzbach *et al.* (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini *et al.* (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record is 1886, with 7 hurricane landfalls, when human influences on the climate were much smaller than they are today.

Table 6.2.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation. While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

Table 6.2.1 Strongest hurricanes to make landfall along the U.S. coast. Source (NOAA HRD(b), 2024)

6.3 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, NCA4 noted that heatwave activity in the U.S. reached a peak in the 1930s (Figure 6.3.1).

AR6: It is *virtually certain* that hot extremes (including heatwaves) have become more frequent and more intense across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe (SPM, A3.1)

AR6: In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA. (Chapter 11, p 1550)

NCA4: Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). (pp. 190-191)

NCA4: Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.** (pp. 190-191)

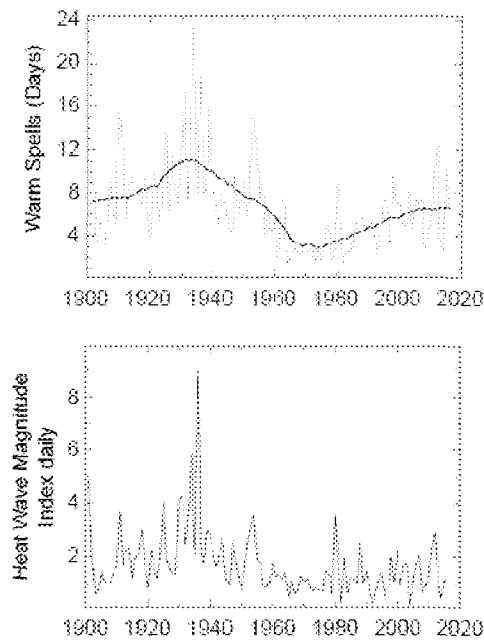


Figure 6.3.1: U.S. Heat waves since 1900. Source: NCA4 Figure 6.4

6.3.1 Temperatures in the U.S. are becoming less extreme

Daily maximum temperatures in the warm season (Tmax, May-Sep) and daily minimum temperatures in the cold season (Tmin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.3.2; Quinlan *et al.* 1987, Karl *et al.* 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves, and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, including unresolved spurious warming due to UHI effects that especially bias Tmin records, this data set is sufficiently accurate for assessing trends in Tmax heat extremes.

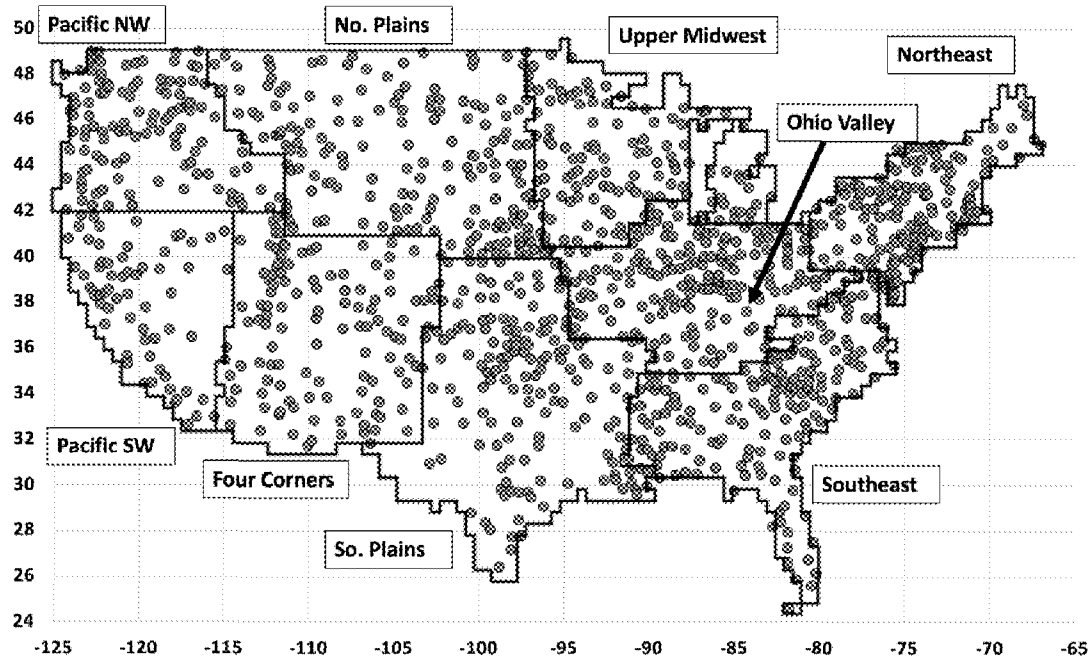


Figure 6.3.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for Tmax would be 1.21 ($=153/126$) per station per year and for Tmin 0.96 ($=122/126$) per station per year.

Figure 6.3.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60 percent of the Tmax records and 59 percent of the Tmin records occurred in the first half of the period (1899-1961).

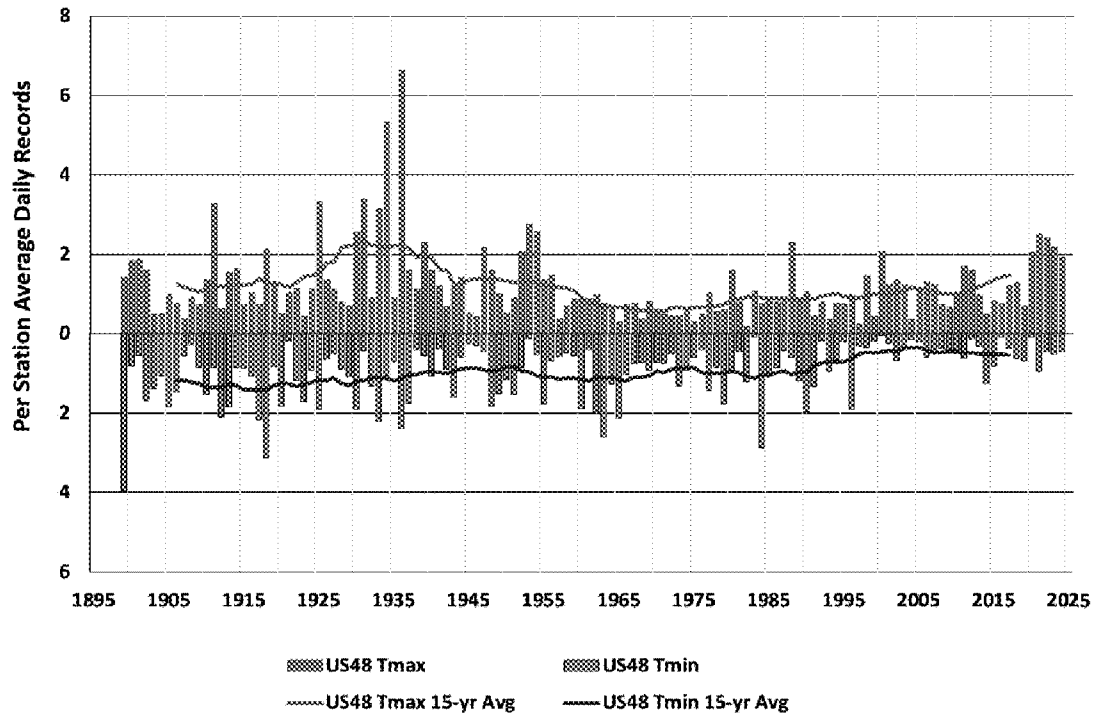


Figure 6.3.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92 percent of observations in the 126-year period since Dec 1898. US48: contiguous U.S. states. Tmax: maximum temperature. Tmin: minimum temperature.

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13 percent of the extreme cold events were measured. In contrast, 25 percent of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA4). Combining the two histories, the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.3.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.3.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

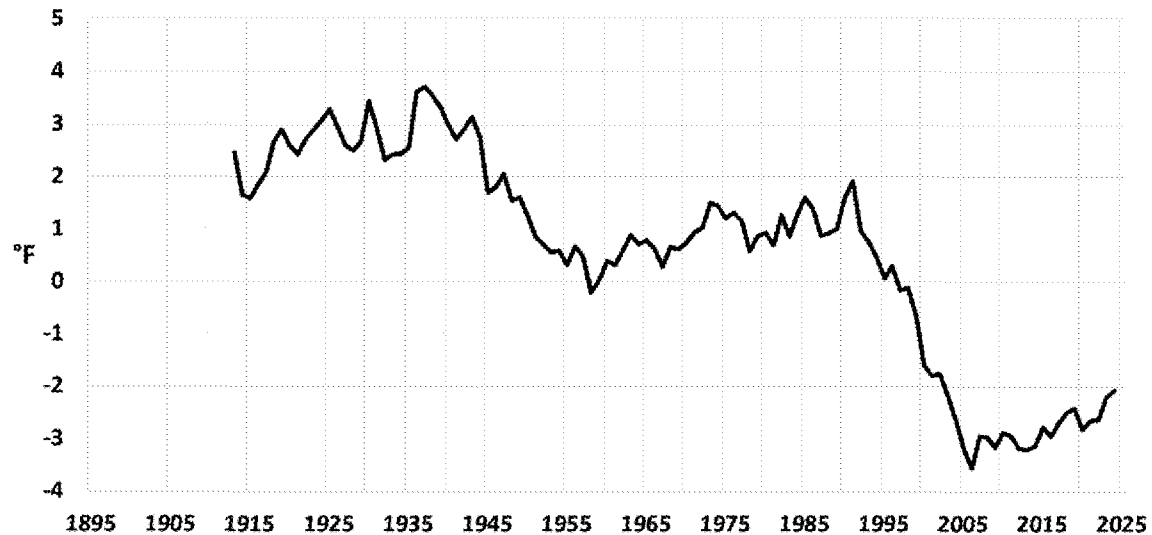


Figure 6.3.4. 15-year trailing average of the difference each year of each station's hottest warm-season Tmax and coldest cold-season Tmin relative to the long-term average. Source: Author analysis of USHCN data.

The average difference for each station between the hottest summer Tmax and coldest winter Tmin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter Tmin, but a decline in summer Tmax is also a factor. The rise in Tmin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Section 3.3 and Spencer *et al.* 2025).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the U.S. climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent U.S. National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

The western U.S. has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the U.S. since 2018, including a record-shattering event in the Pacific Northwest in 2021.

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F Tmax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F Tmax temperatures, a small change will not have much impact on the results.

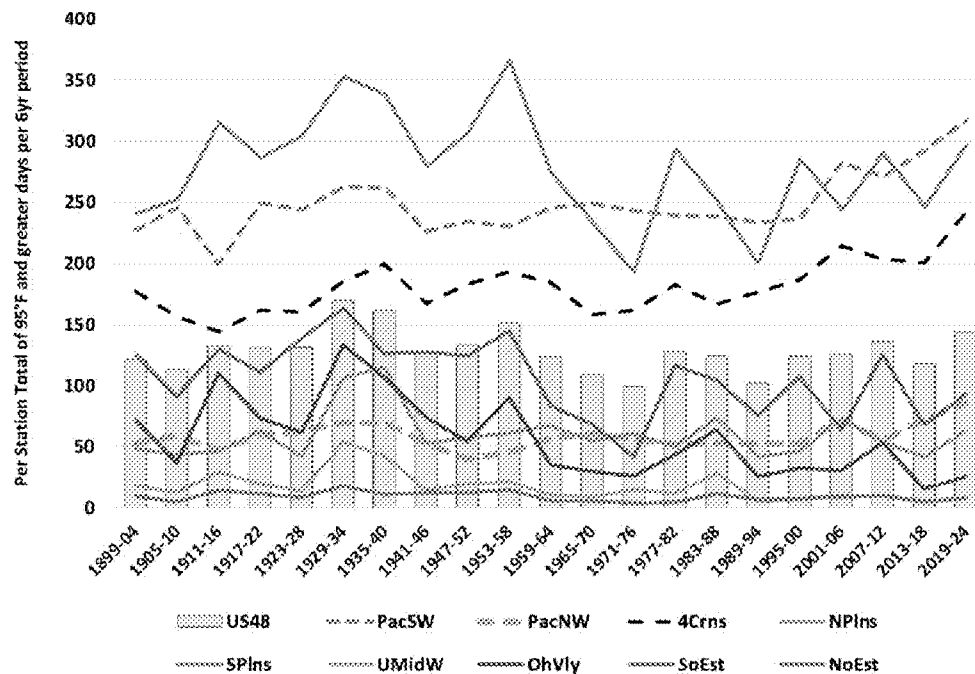


Figure 6.3.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, U.S. 48 (bars) and regions (lines). A 6-year period is used as this evenly divides the 126-year record. US48: contiguous U.S. states. See Figure 6.3.2 for region names. Source: Author analysis of USHCN data.

In the past 126 years, the average CONUS station experienced 129 days exceeding 95°C per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution. Figure 6.3.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA5 quote will be examined more closely in Section 8.6.1. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass *et al.* 2024).

The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA4, except that the reference period here is the entire record 1899-2024 while NCA4 truncated the reference period to 1961-1990, which was a cool interval. That truncation boosts positive results (days exceeding the 90th percentile) in years warmer than the reference period, especially starting in 1960 and moving to the present (see Figure 6.3.6 and discussion below).

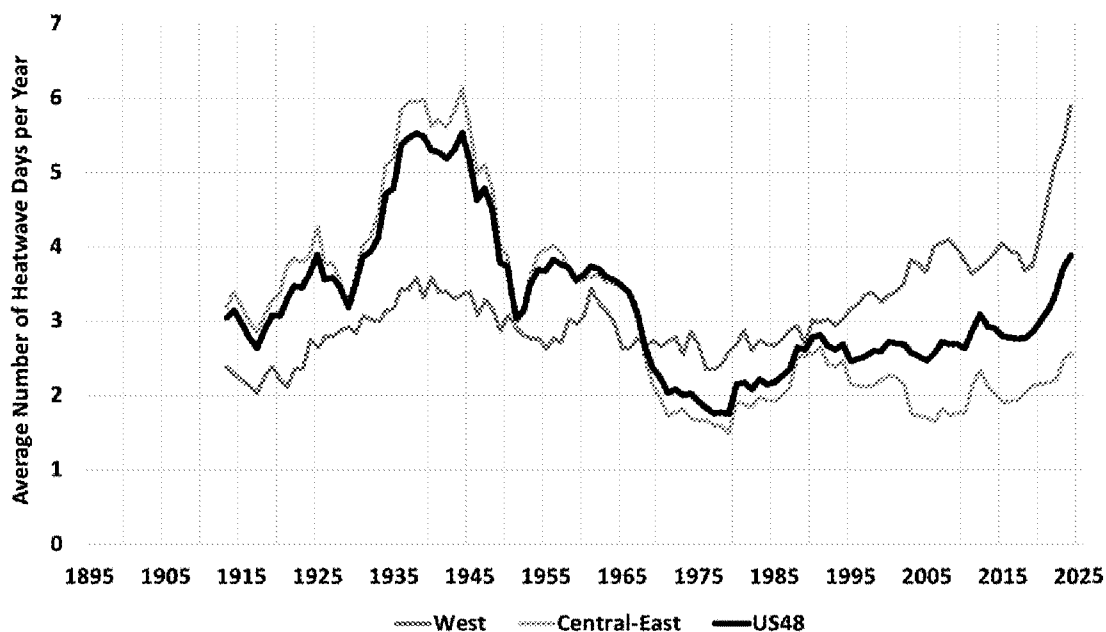


Figure 6.3.6 15-year trailing average of number of heatwave days per year per station in the CONUS (black line) and two regions: West (red), Central-east (green).

Figure 6.3.6 indicates that there are regional variations in heatwave activity. The excessive heat of the first half of the 20th century occurred primarily in the eastern two-thirds of the nation, while the West has seen a recent increase of heatwave days (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA4.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

The analysis of heatwaves is an example of why it is important to consider complete datasets and appropriate metrics. The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.3.7.

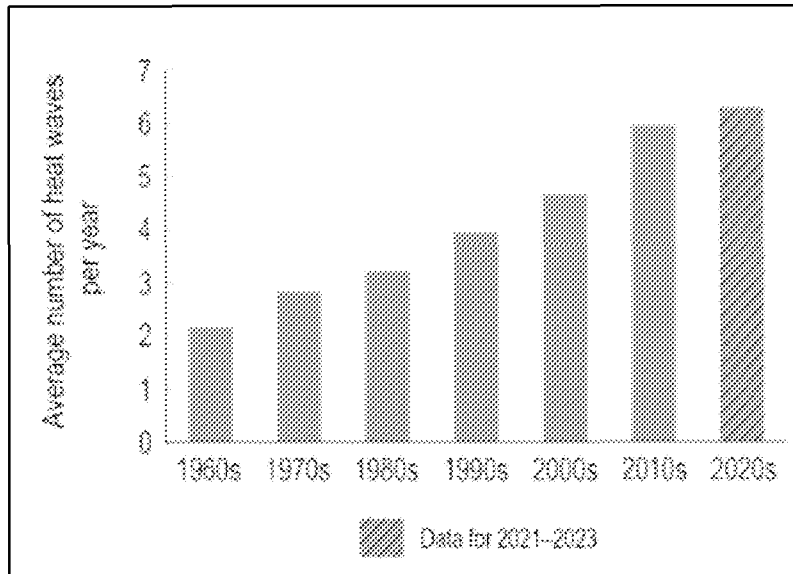


Figure 6.3.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas, a misleading metric for reasons explained in the text. From <https://www.globalchange.gov/indicators/heat-waves> (accessed May 22, 2025).

The figure shows a monotonic increase in each decade from two occurrences per year in the 1960s to six in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the *minimum* apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

Given the unusual heatwave definition and urban focus, these increasing values since 1960 presented in USGCRP (2023) are not informative about long term trends or the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.3.1 and 6.3.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of Tmin relative to co-located Tmax and relative to Tmin at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons that summer Tmax (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy *et al.* 2009). For CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves against the background of urbanization and natural climate variability.

6.4 Extreme precipitation

AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence). (SPM A3.2)

AR6: In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has very likely increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018. (Chapter 11, p. 1560)

The U.S. National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes (Figure 6.3.6).

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast using a trend model with a non-parametric variance estimator robust to the complex autocorrelation properties of precipitation data. When the time series were extended back in time (as far as 1872 in some cases) or started later (1978), there were no significant trends for either region.

These findings have been updated for this report (McKittrick and Christy 2025) with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.4.1. The stations were selected based on availability of long-term high-quality records. The regions are each associated with important features of extreme precipitation behavior: the Pacific coast is associated with landfalling atmospheric rivers for which AR6 cites evidence of increasing activity since 1948 with further increases expected as the world warms (AR6 8.3.2.8.2); the NCA report indicates that the Northeast has experienced the greatest increase in extreme events, and the Southeast is also a place noted in the NCAs as having increased extreme events.

The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.

Pacific Coast heavy rainfall events

- The average precipitation trend is statistically significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov *et al.* 2017, Pan *et al.* 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred during December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter *et al.* 2011).

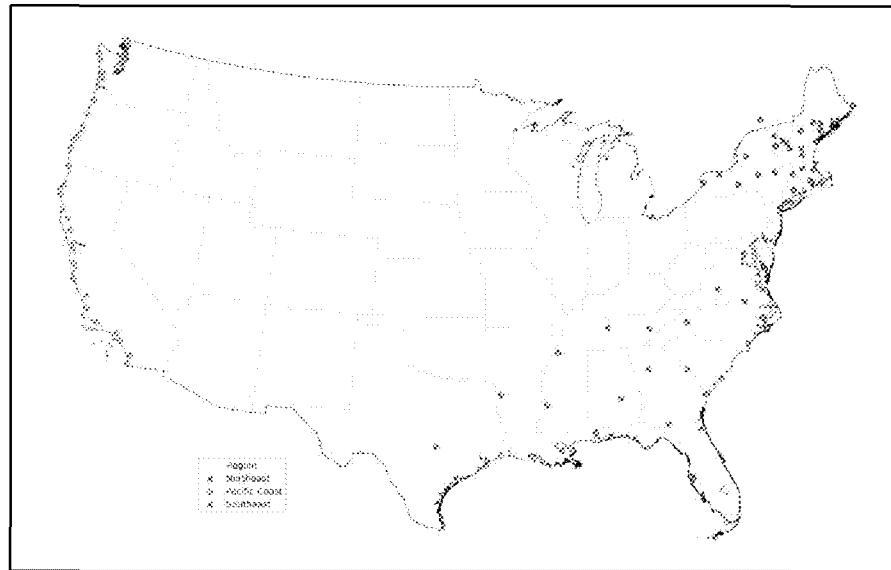


Figure 6.4.1: Locations of precipitation monitoring stations used in this report. Orange: Pacific coast. Blue: Northeast. Green: Southeast. Data from McKittrick and Christy (2025).

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year might have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly spread over the years. In Fig. 6.4.2 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

Southeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in Mobile AL and Quitman GA but insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA but insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.4.3 is analogous to Figure 6.4.2 for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

BOX: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps because of human influences. [Note “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. And comparing the records of the two charts shows the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme listed in Table 6.2
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter *et al.* (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (Section 8.6). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50 percent determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

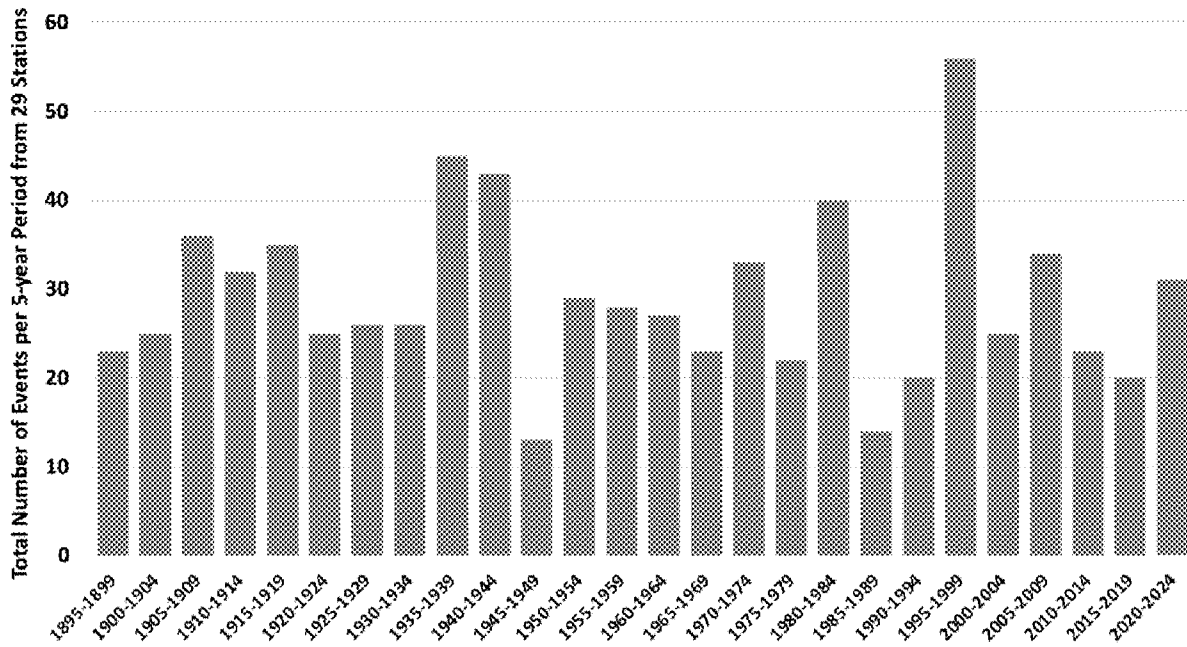


Figure 6.4.2. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

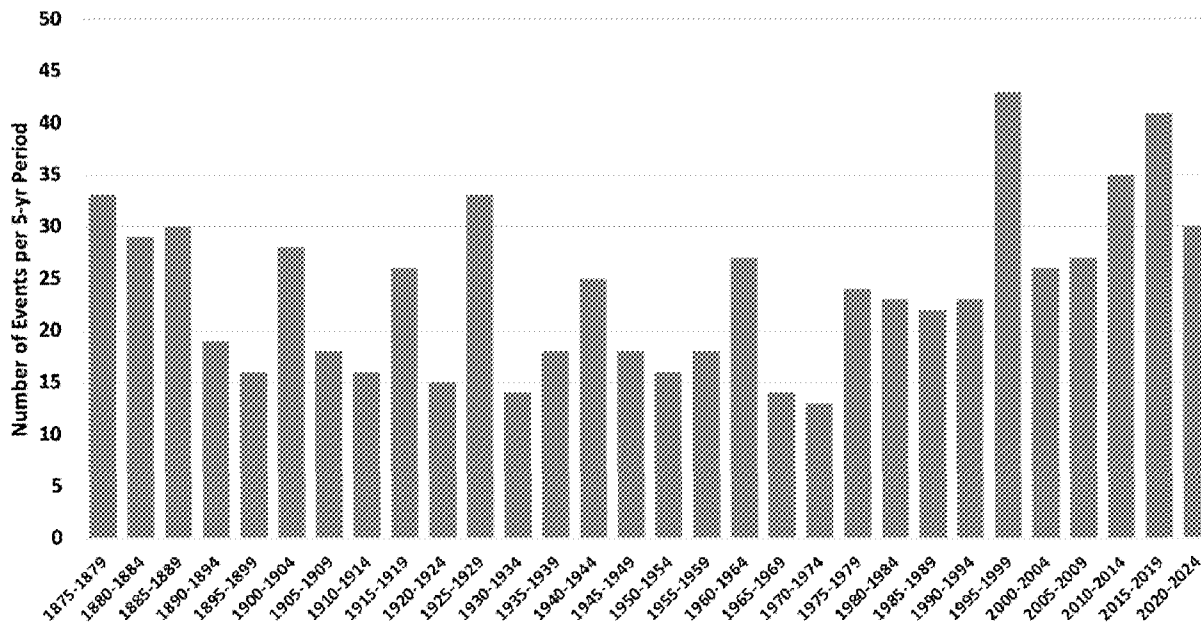


Figure 6.4.3. As in Fig. 6.4.2 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

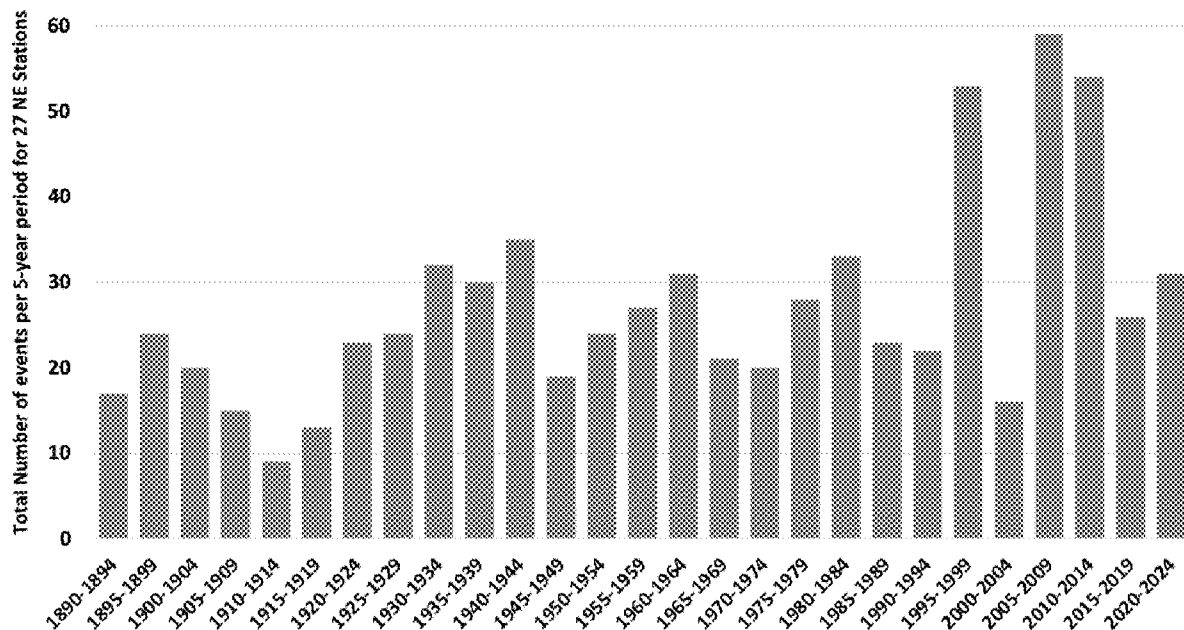


Figure 6.4.4. As in Fig. 6.4.2 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 27 Northeast stations from NY to ME, including Montreal.

Northeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in 12 of 27 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY, Buffalo NY and Eastport ME but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME, Gardiner ME and Eastport ME but insignificant elsewhere.
- When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

Fig. 6.4.4 is analogous to Figure 6.4.2 for the last 135 years in 27 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 77 percent of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it merits a closer examination.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth *et al.* (2019) examined a similar region as in Fig. 6.4.4 that includes PA and NJ and reported significant differences in various precipitation extremes between two 18-year periods, 1979-96 and 1997-2014. That included a 317 percent increase in 24-hr events exceeding 6 inches, while we find a 58 percent increase over the same years. However, Figure 6.4.4 shows that frequency drops sharply after 2014, returning to the long-term average in the subsequent 5-year intervals, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

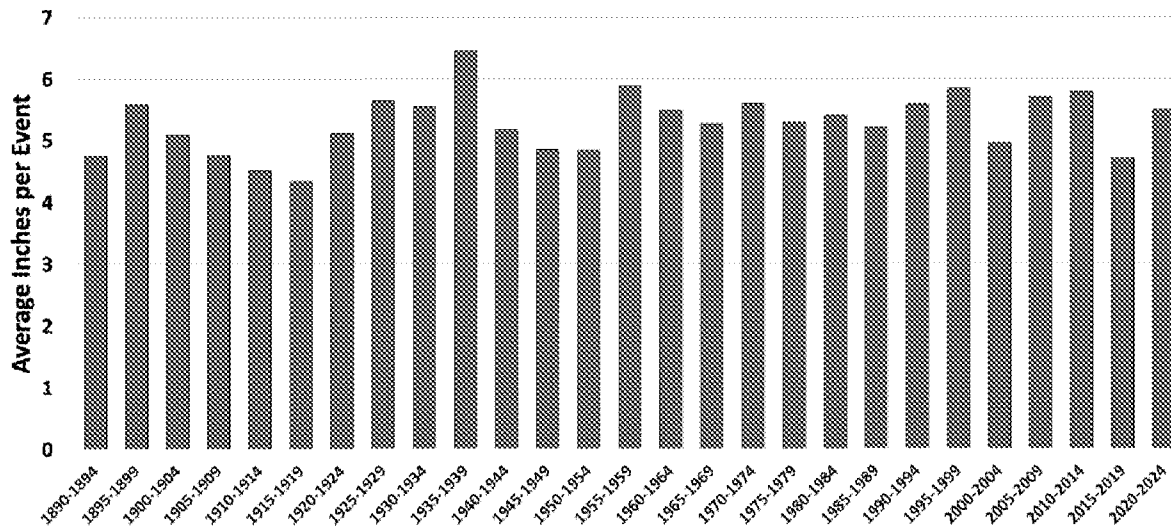


Figure 6.4.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

The high percentage increase in the Howarth *et al.* sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.4.5 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only +0.04 inches/decade. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.4.4 and 6.4.5 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

Jong *et al.* (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded “The autumn extreme precipitation trend over the Northeast U.S. is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: “Was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs?” Jong *et al.* examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.4.5 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events might be redistributed due to the impact of urban infrastructure on the local weather (e.g., Pielke Sr. *et al.* 2011, Zhang *et al.* 2018, Yang *et al.* 2024). Yang *et al.* state “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.4.5.

In summary, some U.S. regions show short-duration increases in extreme precipitation events, consistent with natural variability. But analysis of long term, nationwide historical records that considers the autocorrelation properties of precipitation data does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.5 Tornadoes

AR6 assesses tornado trends in the U.S. as follows:

[O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

The monitoring of weak tornadoes has changed over time. The growth of rural populations and the increasing ability to take video with hand-held devices has led to more frequent reports of weak tornadoes that produce minimal damage. In contrast, strong to violent tornadoes have been observed more consistently over time. Note that tornado strength is measured by the damage it produces, not by the visual appearance of the funnel. Limited real-time observational capabilities in earlier decades did not prevent identification because strong to violent tornadoes leave much more damage which will be assessed later even if the tornado itself was not observed. Since statistics began in 1950, there has been a substantial decrease (by about 50%) in the number of strong to violent tornadoes as shown in Fig. 6.5.1a.

To summarize, there is a noticeable downward trend in the number of severe tornadoes in the U.S. since 1950. After 1990 the number of weak tornadoes in the U.S. has remained roughly constant; data before that are incomplete due to limited monitoring.

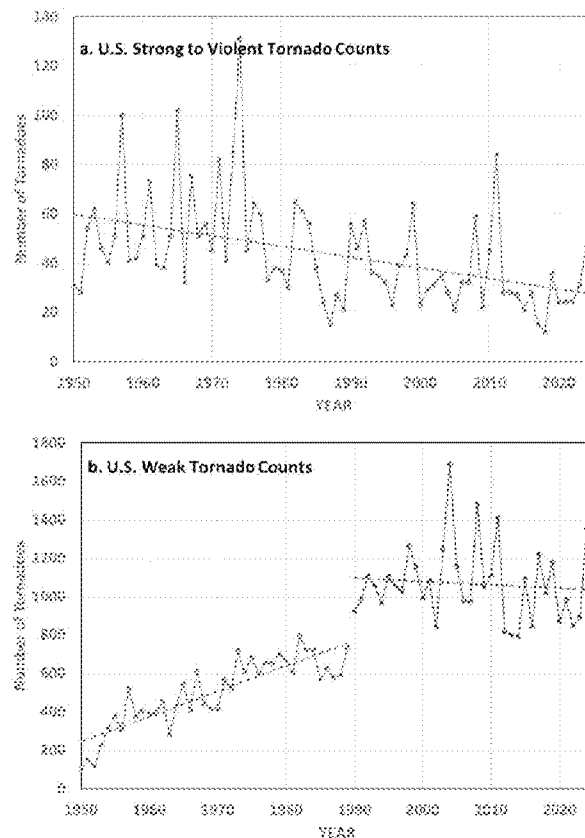


Figure 6.5.1. Annual U.S. tornado counts for (a) strong to violent tornadoes (EF3 to EF5), and (b) weak tornadoes (EF0 to EF2). Based upon NOAA Storms

Prediction Center data, available at https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv

6.6 Flooding

Changes in floods were assessed as follows:

AR6: The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales. (Chapter 11.5)

AR6: [T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*. (Chapter 11.5)

NCA4: Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude **but does not provide robust evidence** that these trends are attributable to human influences (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in Section 6.4 of absence of coherent changes in extreme precipitation.

6.7 Droughts

Assessments of drought trends were as follows.

AR6: Few AR6 regions show observed increases in meteorological drought (Section 11.9, p. 1575),

AR6: Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions. (Chapter 11 Summary)

NCA4: As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined**. (p. 233)

NCA4: Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence). (p.231)

SREX: From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia. (p. 170)

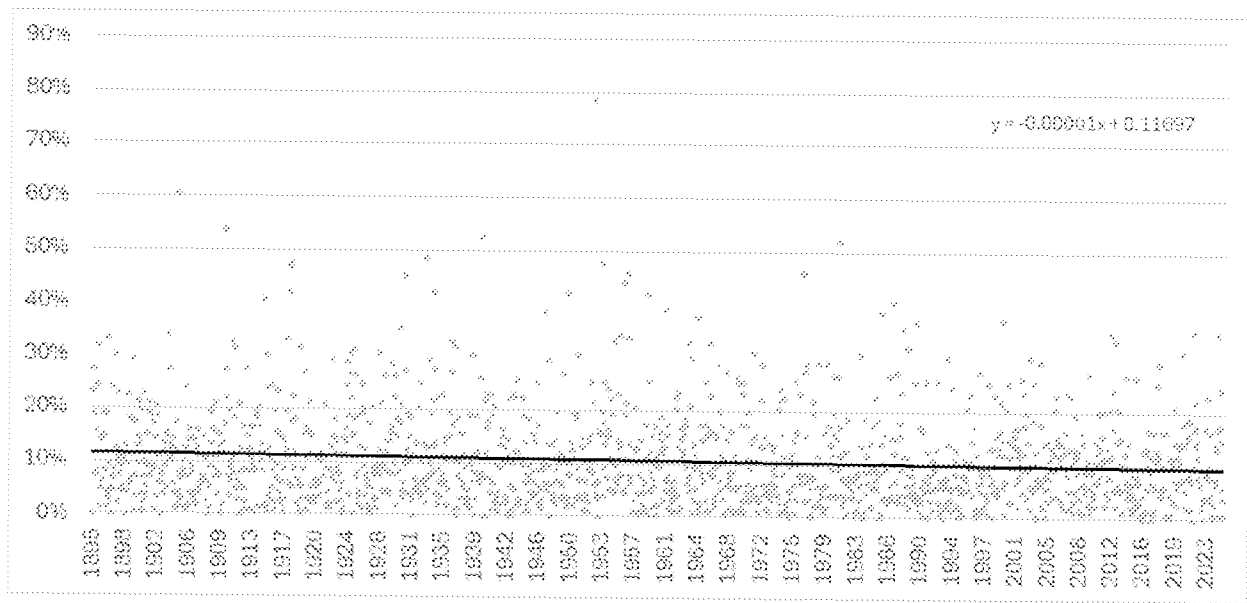


Figure 6.7.1: Monthly percent of US classified as “Very Dry” 1895—2025. Data source: NOAA <https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0> least squares trendline added.

As shown in Figure 6.7.1, U.S. long-term data shows an insignificantly declining trend in extreme dryness (-0.001 percent per year)

Kogan *et al.* (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

In summary there is no evidence of increasing drought frequency or intensity in the U.S. or globally over recent decades.

6.8 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.8.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.

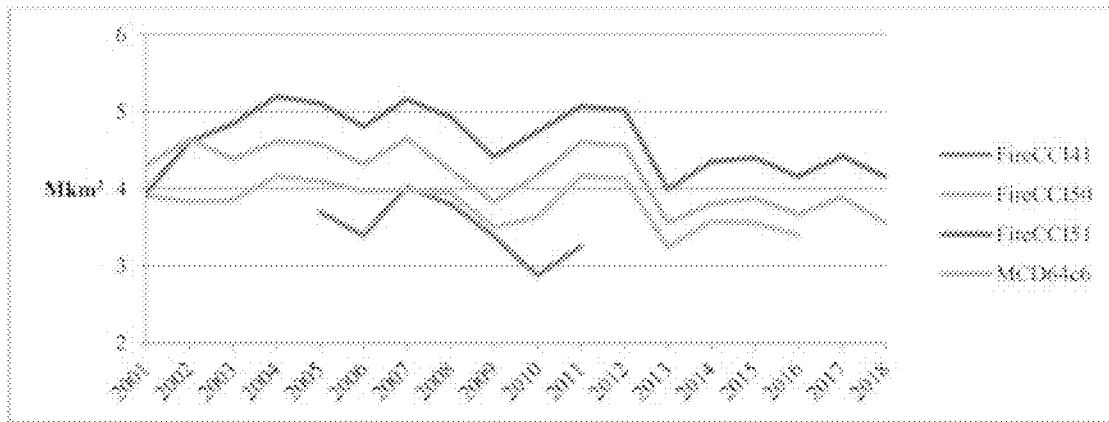


Figure 6.8.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola *et al.* (2021) Figure 12. The different coloured lines represent data products derived from different satellites and algorithms

Global data show that wildfire coverage is constant or declining on every continent (Samborska and Ritchie, 2024).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. Paleoclimatic evidence indicates that past activity was much higher than today. Marlon *et al.* (2012) used sedimentary charcoal layers to reconstruct fire history of western U.S. for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.8.2 below (from Figure 2 in their paper). There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks *et al.* (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

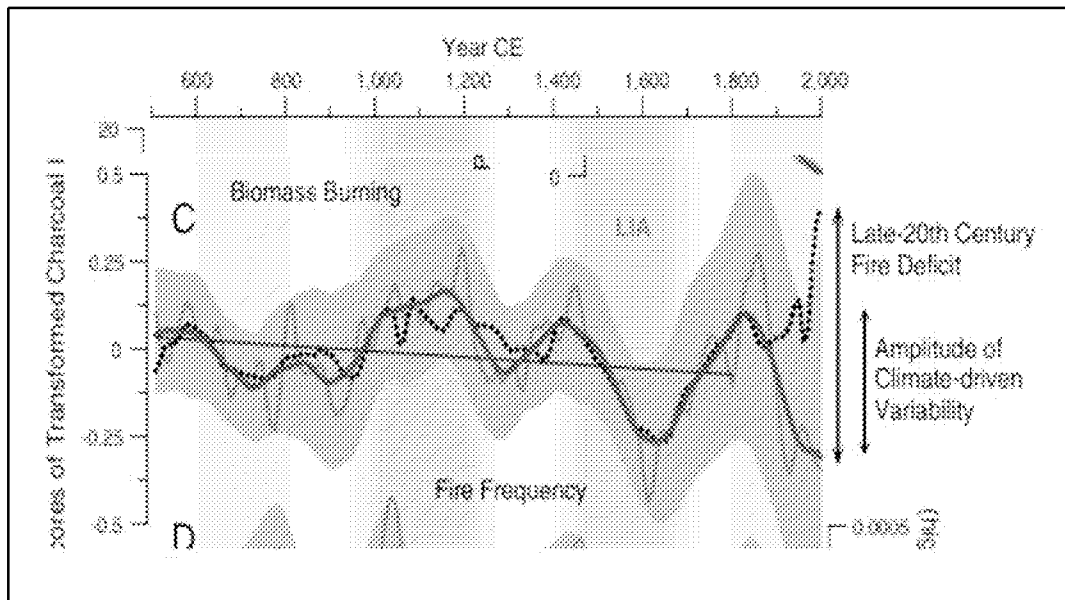


Figure 6.8.2 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on climatic conditions. Source: Marlon *et al.* (2012) Figure 2.

U.S. data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.8.3. The NIFC has removed the pre-1960 data from its current website on the grounds that measurement methods changed after 1960 making the comparison unreliable. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life, including humans. Science has confirmed the overall benefit and necessity of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile U.S. forest fire remains the 1910 Big Blowup fire in the U.S. west, which destroyed over three million acres and eliminated entire towns like Taft, MT (Apple, 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal of defeating all forest fires (Forest History Society, 2022). This led to the “10 am rule” in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation, 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (U.S. Forest Service, 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and controlled wildfires are more appropriate (Sommer, 2016). Recent research is validating this approach and recognizing that more frequent smaller fires likely result in healthier forests, water ecosystems and biodiversity (Stephens *et al.*, 2021).

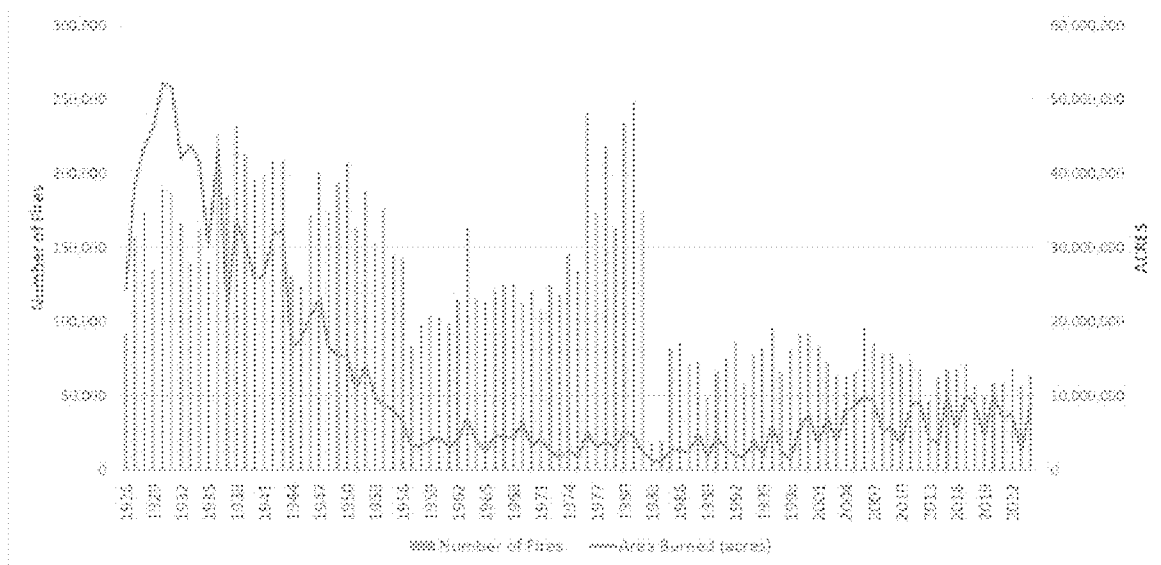


Figure 6.8.3: U.S. wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Center data <https://www.nifc.gov/fire-information/statistics/wildfires>. Pre-2017 webarchive.org (n.d.).

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7 CHANGES IN SEA LEVEL

Chapter Summary

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also with ocean circulation patterns. The largest sea level increases along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothetical ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the interval has elapsed by 2025, with sea level rising at a lower rate than predicted. U.S. tide gauge measurements reveal no obvious acceleration beyond the historical average rate of sea level rise.

7.1 Global sea level rise

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (Fox-Kemper *et al.*, 2021). The rate of global sea level rise is estimated to be 0.12 inches/year, about the height of two stacked pennies (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters in 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860, well before most anthropogenic greenhouse gas emissions.

7.2 U.S. sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 7.1 shows that in Canada and Alaska (and also northern Washington), sea level is decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show low rates of sea level rise, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

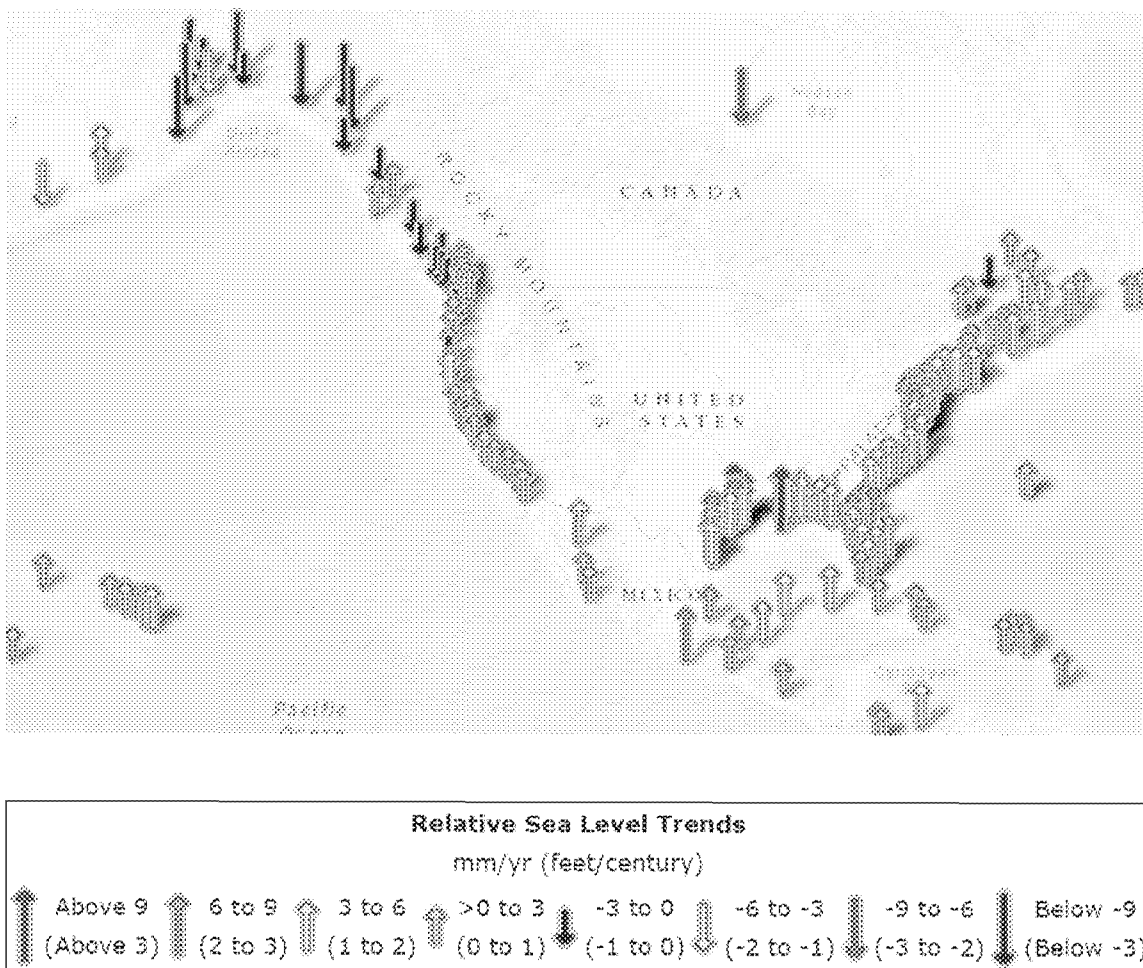


Figure 7.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. The latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (Wöppelmann and Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (*e.g.* for urban development) and subsurface extraction of groundwater or hydrocarbons.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; Letetrel *et al.*, 2015; Karegar *et al.*, 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

Table 7.1 Absolute sea level rise (inches/year) consisting of Relative Sea Level Rise (RSLR) plus Vertical Land Motion (VLM)

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.2). As shown in Table 7.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (Shirzaei and Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, are caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

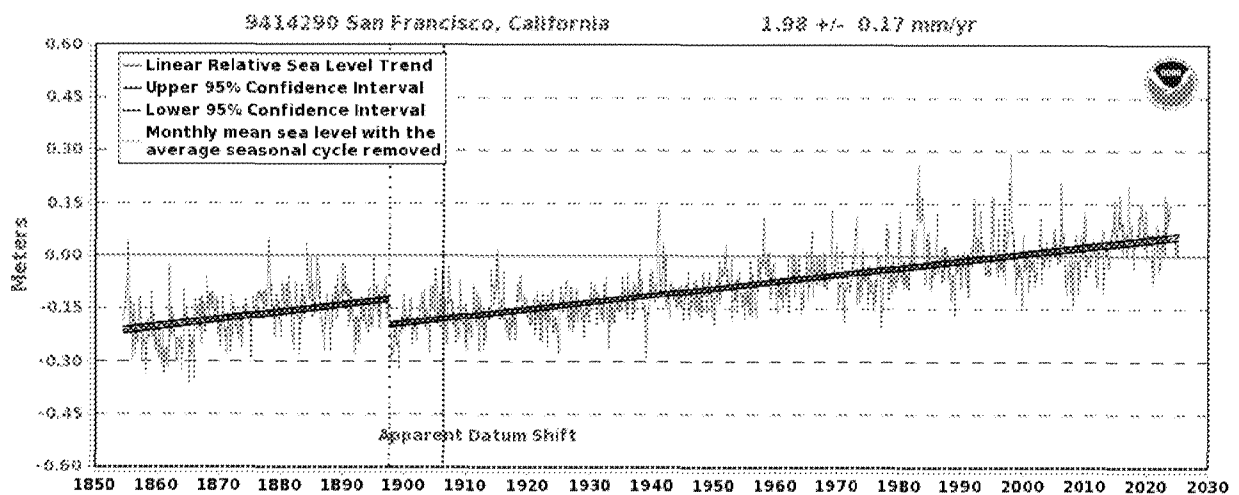


Figure 7.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (Kasmarek and Ramage 2017), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

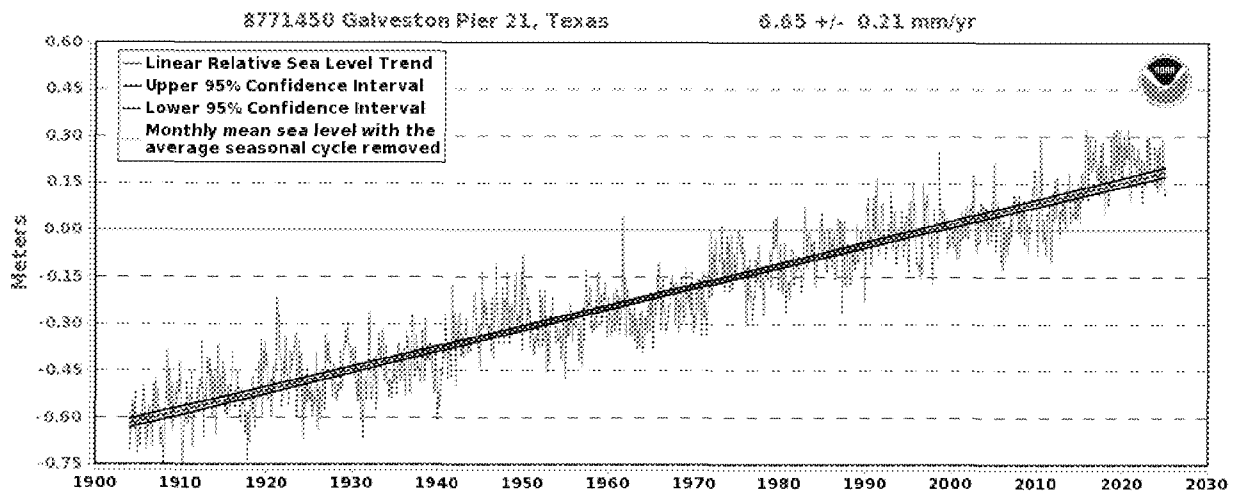


Figure 7.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 7.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 7.1 gives the absolute sea level rise as +0.08 inches/year.

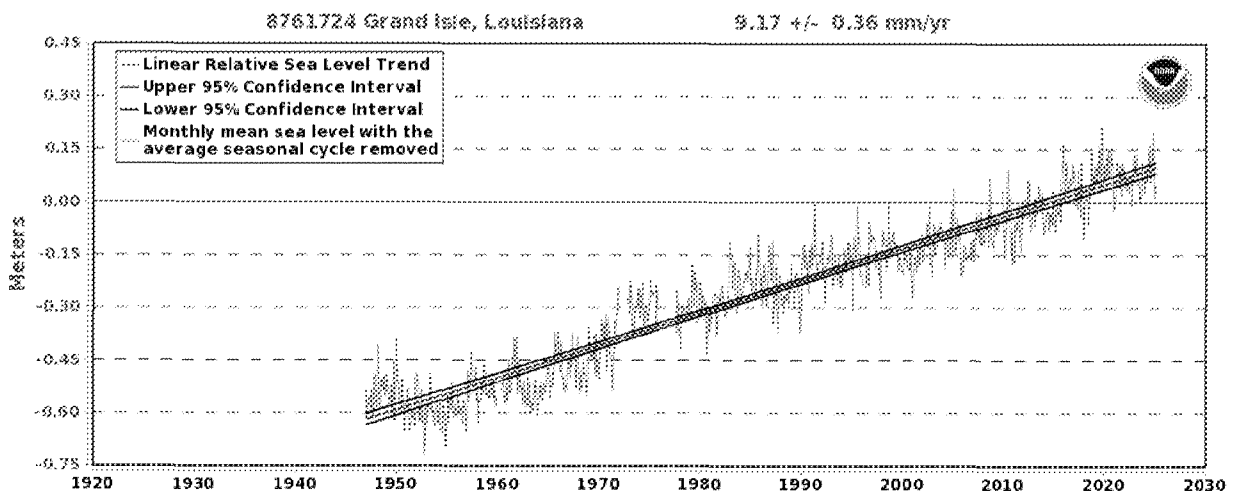


Figure 7.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi River being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi’s suspended sediment load by ~50 percent (Maloney 2018). A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (Neinhuis *et al.* 2017), associated with groundwater and resource withdrawal. As the city’s elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans’ problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (The Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55 percent of the measured relative sea level rise.

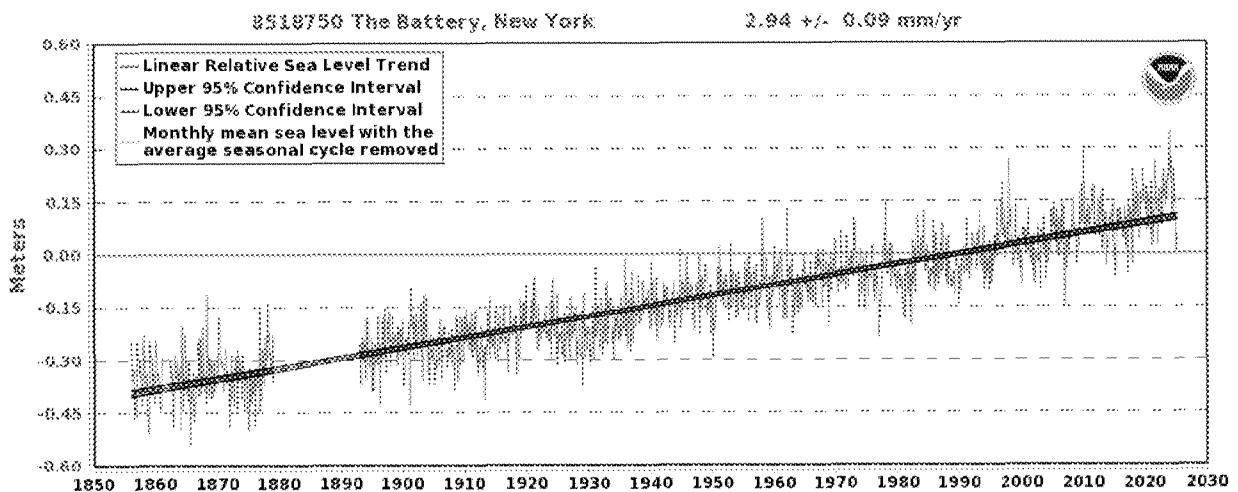


Figure 7.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

7.3 Projected sea level rise

The concern over sea level rise is not about the roughly eight inches of global rise since 1900. Rather, it is about projections of *accelerated* rise based upon simulations of a warming climate through the 21st century.

AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (Fox-Kemper *et al.*, 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (Fox-Kemper *et al.*, 2021). There is deep uncertainty surrounding projections of sea level rise to 2100 owing to uncertainties in ice sheet instabilities, particularly for the higher emissions scenarios.

In February 2022, NOAA issued its projections of sea level rise for various sites along the U.S. coast (Sweet *et al.*, 2022). They claim that by 2050, the sea will have risen one foot at The Battery in Manhattan (relative to 2020). A one-foot rise in thirty years would be more than twice the current rate and about three times the average rate over the past century. In that historical context, NOAA’s projection is remarkable—as shown in Figure 7.6, it would require a dramatic acceleration beyond anything observed since the early 20th century. But even more noteworthy is that Sweet *et al.* (2022) say this rise is “locked in”—it will happen no matter what future emissions are. We should know in a decade or so whether that prediction has legs.

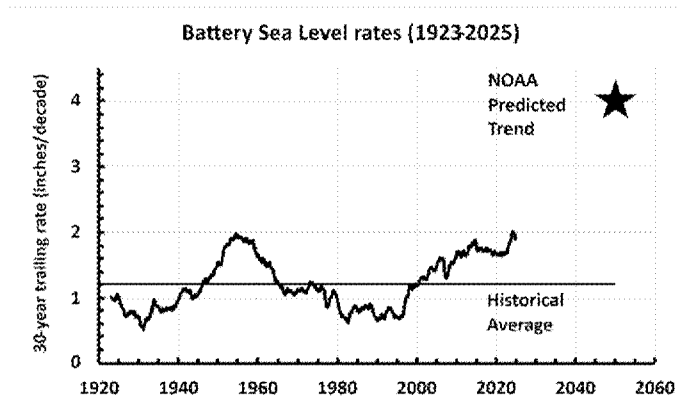


Figure 7.6 Rate of sea level rise at the Battery in Manhattan. Shown is the historical thirty-year trailing trend, together with the allegedly “locked in” NOAA predicted trend for 2050. Historical data: NOAA Tides and Current.

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8 UNCERTAINTIES IN CLIMATE CHANGE ATTRIBUTION

Chapter summary

“Attribution” refers to identifying the cause of some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and in aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (*e.g.* event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the AR6 WGI Glossary (IPCC, 2025):

Detection: Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.

Attribution: Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.

Both detection and attribution rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities (such as GHG emissions) versus natural factors (like volcanic eruptions) contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl *et al.*, 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer *et al.*, 2014) makes the following statement:

Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key IPCC attribution methods.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model is weighted to try to minimize the influence of random noise and the estimation method is chosen to account for climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (*e.g.* heat waves or droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: **Most of the observed increase** in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations. (IPCC 2007)

AR5: It is *extremely likely* that **more than half of the observed increase** in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period. (IPCC 2013)

AR6: The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that **well-mixed GHGs were the main driver** of tropospheric warming since 1979. (IPCC 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began increasing rapidly. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99 percent of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850–1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 5, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

AR6 states that natural external drivers since 1850–1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850–1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulations.

Solar variability

AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m², Myrhe *et al.*, 2014). AR6 acknowledges substantially higher values and a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by 0.7–2.7 W/m², a range that includes both low and high variability TSI data

sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact of solar forcing on the climate was still assessed to be small compared to anthropogenic forcing. However, the impact of solar variations on the climate is uncertain and subject to substantial debate (Lockwood, 2012; Connolly *et al.*, 2021) - something that is not evident in the IPCC assessment reports.

The variations of TSI over time remains a challenging problem. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets that disagree as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models that infer past solar variations from sunspots and cosmogenic isotope measurements (Velasco Herrera *et al.*, 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos *et al.*, 2023; Solanki *et al.*, 2004; Usoskin *et al.*, 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70 percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta *et al.* (2023) suggests that ~80 percent of solar influence on climate might stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models have too little amplitude compared to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov *et al.* 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (*e.g.* CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the AR5 and AR6 reports:

AR5: Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.

AR6: Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (*high confidence*).

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to $+0.2^{\circ}\text{C}$ (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C . Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out owing to differences in phasing, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 (Figure 8.1) shows irregular variations of significant amplitude against the background of an overall warming trend and, after 1976, a pronounced difference in trends between the Northern Hemisphere and the Southern Hemisphere. The period between 1905-1945 shows a strong trend of warming. The following 30 years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

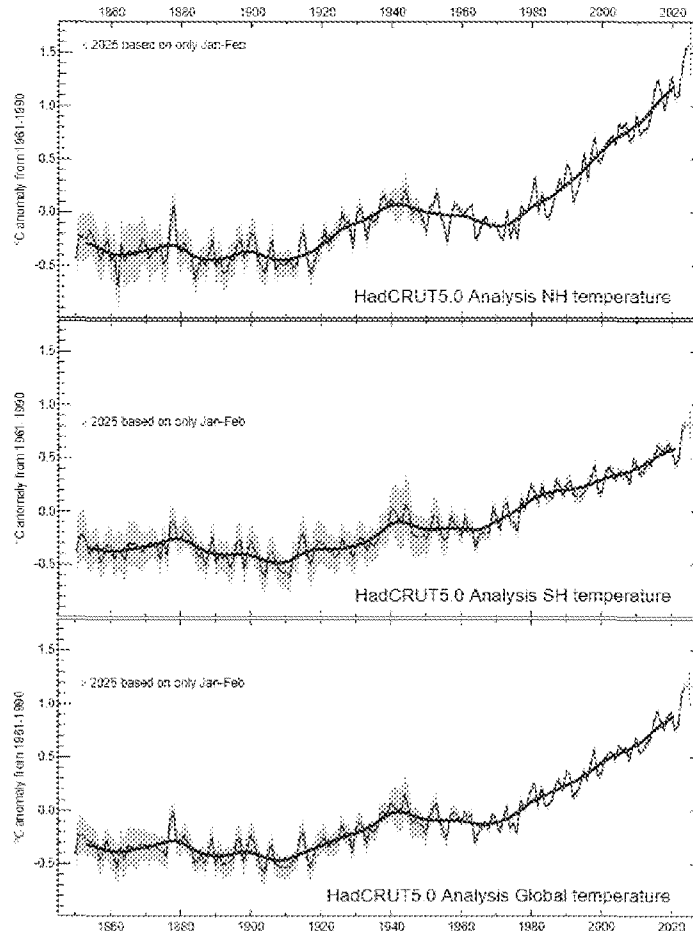


Figure 8.1 Global average surface temperature anomalies 1850—2025. Top: Northern hemisphere. Middle: Southern hemisphere. Bottom: Global average. Source: UK Hadley Centre <https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf>

The causes of the early 20th century warming are discussed by Hegerl *et al.* (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941, implying that CO₂ had little impact. Volcanic activity during this period was very low, and solar forcing is uncertain. Yet Hegerl *et al.* (2017) somehow inferred that 40-54 percent of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman *et al.* (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid-century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that these variations were most likely caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity, as well as growing greenhouse gases concentrations. Tokinaga *et al.* (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic

warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale circulations over the Northern Hemisphere; these same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson *et al.* (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns, including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean *et al.*, 2009; Tung and Zhou, 2013; Chylek *et al.*, 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or “fingerprints”) associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares (TLS). The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001, there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2021, 2022, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2021) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen *et al.* (2023) confirmed this analysis, although they argued that the method could yield valid results under very stringent assumptions. McKittrick (2022) and (2023) raised a further concern that climate scientists—virtually alone among

scientific disciplines—have used TLS to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unstable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS estimates have a large positive bias. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the attribution.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2023) using a different estimation method and multiple independent data sets.

While these analyses do not falsify results of the IPCC optimal fingerprinting method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades *et al.*, 2016, Balcombe *et al.*, 2019, Dagsvik *et al.*, 2020, Razzak, 2022, Dagsvik and Moen, 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable, we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson *et al.* (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data, the coherence in the series is primarily due to the influence of temperature on CO₂ levels, not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time

series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also increased abruptly in recent years. The question is whether the change is an internal feedback to warming caused by greenhouse gases, or whether something else increased the fraction of absorbed radiation which then caused the recent warming.

The planetary albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important in this regard. The Earth's albedo is approximately 30 percent, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in planetary albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.2 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5 percent reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in absorbed solar radiation averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Goessling *et al.* (2025) assessed that the planetary albedo was relatively low around the 1940's and 50's before rising industrial aerosol precursor emissions increased the albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum might have been the lowest since at least 1940.

Changes in surface characteristics cannot explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5 percent since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England *et al.*, 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that “There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability.” (Summary for Policymakers, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer, see <http://climate.rutgers.edu/snowcover/> and Section 5.6
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo decrease associated with increasing forested area.

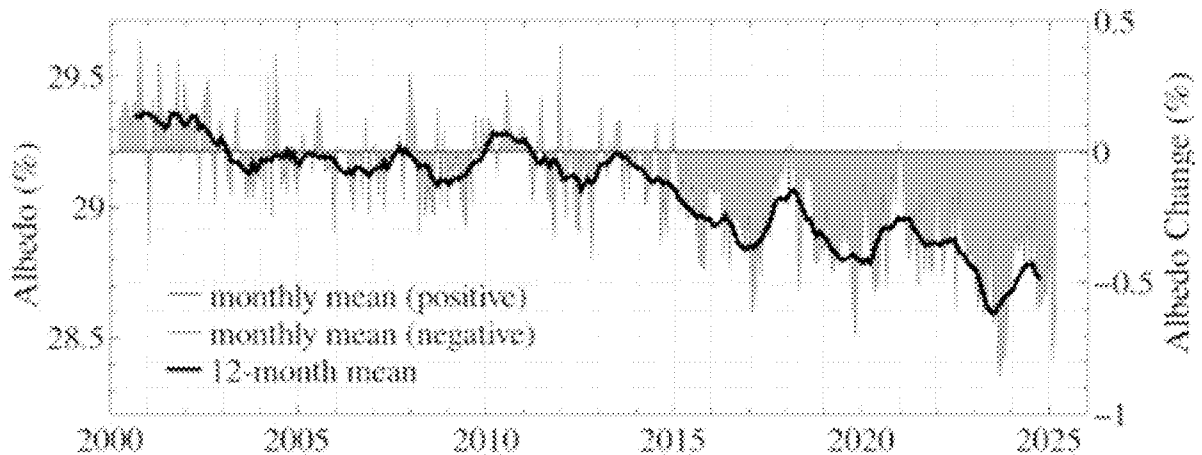


Figure 8.2. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor of three on average, primarily due to cloud masking (Loeb *et al.* 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally. This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (*e.g.* dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall might produce less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog *et al.*, 2024; Yuan *et al.*, 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

Changes in clouds are the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb *et al.*, 2024; Goessling *et al.* 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb *et al.* found that decreases in low- and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Goessling *et al.* (2024) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The issue then becomes the cause of the change in cloud cover. Two explanations have been posited for the declining cloud cover over the past decade:

- Natural climate variability

- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

It is not easy to justify a new positive low cloud feedback that began emerging in 2015. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was one of the strongest El Niño events on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams *et al.*, 2017; Arthun *et al.* 2021).
- The Pacific Decadal Oscillation positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO) have a significant global signal and strong regional signals, especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Goessling *et al.* (2024) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz *et al.*, 2025; Kuchar *et al.*, 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of the Hunga Tonga eruption on the planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1- 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the recent trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and for the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe *et al.* 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold,” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC

also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first columns Table 12.12 in Ranasinghe *et al.* (2021, p. 1856), reproduced here as Table 8.1, summarize the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Out of the 33 weather impact categories listed, an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Further, two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, or drought.

Other columns of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here: whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer and Stevens 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan et al, 2019). Even with these caveats, we note that the omitted columns in AR6 Table 12.12 show most weather impacts are not expected to exhibit an anthropogenic signal through the end of this century.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	4
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Acidity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fair weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	11
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwaves	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease	Medium confidence of decrease	Low confidence is direction of change	Medium confidence of increase	High confidence of increase
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Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

As discussed in Chapter 6 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that it is not currently possible to attribute changes in most extreme weather types to human influences. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.6 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between its chapters. Chapter 11 of WG1 states (Seneviratne *et al.*, 2021):

Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.

By contrast, as noted in Section 8.5, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare an event in today's climate with one in a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100 percent of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.

Because EEA is relatively new, many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the U.S. National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 6, many of the worst extreme weather and climate events in U.S. history occurred in the first half of the 20th century, including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass thresholds of what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean that a climate change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an “ordinary” weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second “heatwave” regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh *et al.* (2015) both point out that different distributions might fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis, drawing a connection between individual events and global climate change should be avoided. Furthermore, the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow *et al.*, 2020). Methods to eliminate the bias have not yet been established, leading some experts (*e.g.* Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain that it should be avoided altogether.

We provide a case study of a recent high impact extreme event in the U.S. to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.6.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme event that affected much of Western North America in late June 2021. Surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass *et al.*, 2024).

The WWA team generated international headlines with their analysis, which provided the following attribution statements (WWA, 2021; Philip *et al.*, 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a one in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important counter to the first claim is that other researchers concluded from historical weather data that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman, 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman, 2023, p. 49).

Mass *et al.* (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking mid-tropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking mid-tropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass *et al.* assessed that there was no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming might have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

Bercos-Hickey *et al.* (2022) conducted a statistical analysis of a model-based attribution study of this heat wave. Because the event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave - they provided a more highly constrained estimate that human activities caused a ~1.4°F–1.8°F increase in the daily maximum temperatures.

Zeder *et al.* (2023) also concluded that the methods employed by Philip *et al.* (2022, the WWA analysis) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analyses showed that the event was caused by rare meteorological conditions that were not made more probable by global warming.

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PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

9 CLIMATE CHANGE AND U.S. AGRICULTURE

Chapter summary

There has been abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. The increase in ambient CO₂ has also boosted productivity of all major U.S. crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from, or be harmed by, climate change, once the adaptative responses of farmers are considered the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn *et al.* (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn *et al.* method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached conclusions similar to Mendelsohn *et al.* (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the U.S. agricultural sector. However, a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in U.S. agriculture due to climate warming.

Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and

20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2, CO₂ is a major driver of plant growth, so this omission biases the analysis towards underestimation of the benefits of climate change to agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiments” or FACE plots, in which small sources of CO₂ are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth *et al.* (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm caused an average 18 percent increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key U.S. agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations improved photosynthesis rate, water use efficiency, and growth Li (2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. There were also ten studies reporting on +600 ppm CO₂ enrichment, which increased photosynthesis by an average of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr., 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41 percent loss of growth under ambient CO₂ but only a 13 percent loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured both the yield and nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16 percent but a 7 percent decrease in grain protein levels. But they also found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection, growers could select wheat types that best take advantage of the elevated CO₂.

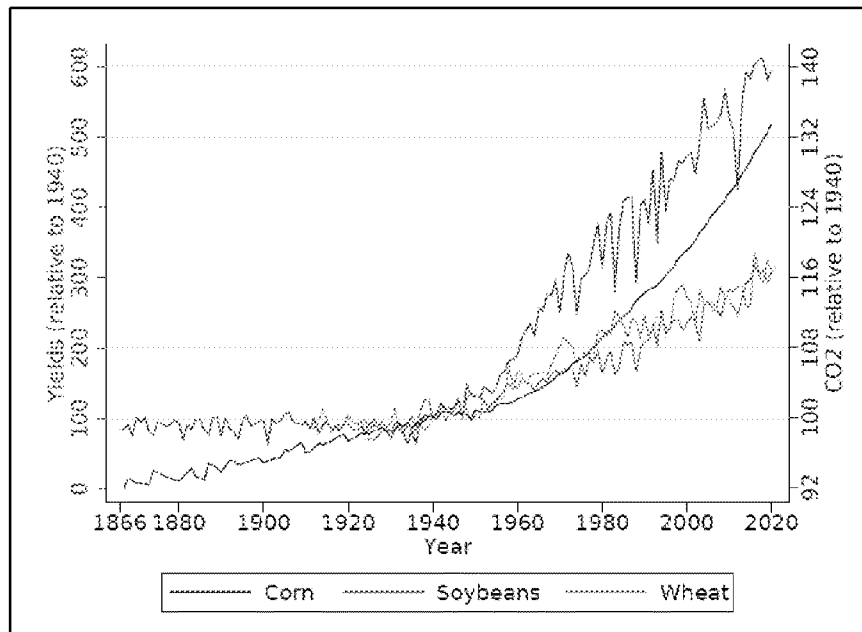


Figure 9.1: U.S. average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100. Source: Taylor and Schlenker (2021)

Further evidence

A 2021 report from the U.S. National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted U.S. crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

Beyond growth benefits, extra CO₂ boosts plant resilience to dryness. Deryng *et al.* (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for maize (corn), wheat, rice and soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them; once fertilization was taken into account, all regions showed a net CWP gain. Deryng *et al.* also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains and mitigated by up to 90 percent for rice and 60 percent for maize. Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng *et al.* (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, observations show the opposite: greening is happening even in arid areas. Zhang *et al.* (2024) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4 percent of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the U.S. Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based largely on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore *et al.*, 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore *et al.* (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore *et al.* projected declining global crop yields for all crop types in all regions due to warming.

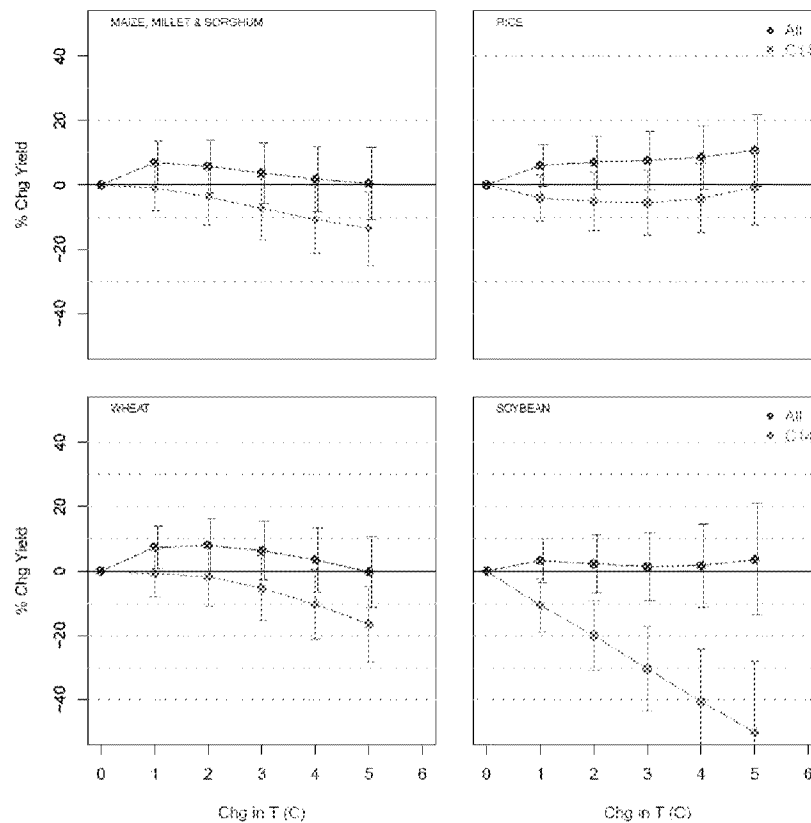


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore *et al.* (2017). Green: after including omitted data. Source: McKittrick (2025).

McKittrick (2025) re-examined the Moore *et al.* database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the records most commonly missing were the changes in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables, thereby increasing the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 9.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

9.4 CO₂ fertilization and nutrient loss

Evidence has shown that CO₂-induced biomass gains are sometimes accompanied by reductions in the concentrations of protein and other key nutrients such as iron and zinc (Ebi *et al.* 2021). Some experimental evidence has shown that the rising temperatures expected to accompany higher CO₂ levels will offset this loss (Köhler *et al.* 2019) although the evidence for this is mixed, as is the evidence that nutrient dilution observed to date is attributable to higher CO₂ (Ziska 2022). If nutrient dilution does occur under rising CO₂ levels there are several adaptive strategies that could be pursued.

First, selective breeding to raise micronutrient content is already long established (Saltzman *et al.* 2017) and has proven to be a cost-effective agronomic strategy (Ebi *et al.* 2021). Strategies can include both conventional breeding and genetically-modified organisms. An example of the latter is Golden Rice, which contains elevated levels of beta-carotene to boost biosynthesis of vitamin A in the human body. Optimal strategies will be location-specific because they vary by crop, climate and soil type (Ebi *et al.* 2021). Second, fortification of food products with micronutrients is already routine. Folic acid (a B vitamin) is added to flour and many other foods; iodine is added to table salt, most commercial breakfast cereals are fortified with iron and numerous vitamins, *etc.* Third, dietary supplements in the form of multivitamin tablets are inexpensive, widely-available and routinely consumed.

One concern about reliance on adaptive strategies is whether they are feasible in low-income countries. Micronutrient deficiency is already a problem in the developing world and dietary supplements have proven to be an effective low-cost response (Ebi *et al.* 2021). It should also be noted the IPCC emission scenarios that generate high levels of warming do so on the basis of high levels of income growth. The SSP scenarios³ assume that, compared to 2005 levels, global per capita income will double by 2100 in the lowest growth case (SSP3), and in the highest emission case (SSP5) global per-capita income will grow nearly 16-fold. In that scenario even the poorest regions (Africa and the Middle East) end up with a per capita income of about US\$126,000, 70 percent higher than current U.S. per capita income (about US\$75,000). Consequently the same scenarios in which CO₂ levels increase the most are also those in which global poverty is largely eliminated, in which case all countries would be able to afford dietary supplements as necessary to address micronutrient deficiencies, if they arise and cannot be addressed using on-farm agricultural strategies.

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. To the extent nutrient dilution occurs there are mitigating strategies available that will need to be researched and adapted to local conditions.

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³ See compilation at [Our World in Data](#).

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10 MANAGING RISKS OF EXTREME WEATHER

Chapter summary

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The U.S. economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase if people are able to undertake adaptive responses.

10.1 Socioeconomic context

Risks from human-caused climate change are affected by natural weather and climate variability and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as U.S. population grew from 76 million in 1900 to over 331 million in 2020 (Goklany 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01 percent of the U.S. population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006 percent of the U.S. population) (NOAA National Hurricane Center 2025; U.S. Census Bureau 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang 2023). U.S. weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (Molina and Rudik 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992), have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (Battelle Memorial Institute 2013). Inland dams in the U.S. help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1 Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the U.S., so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster as a proportion of GDP have decreased by about 80 percent since 1980, as shown in Figure 10.1. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments, NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (Pielke Jr., 2025).

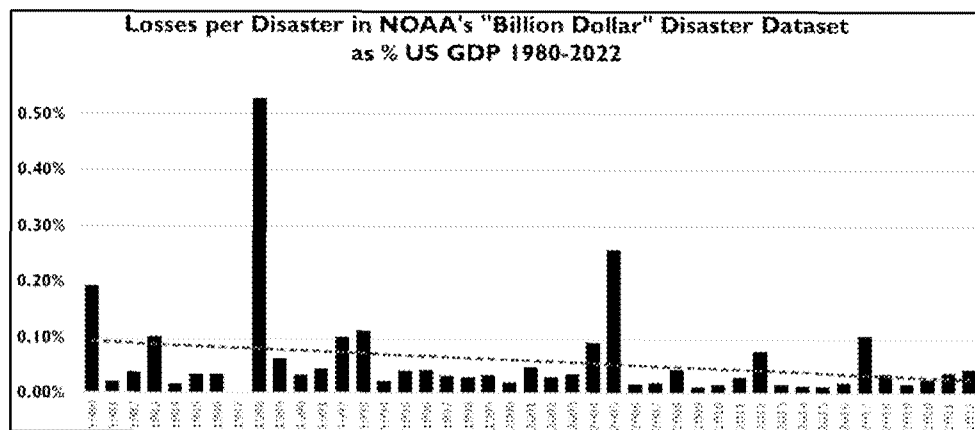


Figure 10.1: Losses per disaster as a % of Gross Domestic Product in NOAA's billion-dollar disaster dataset (the version downloaded in July 2023), 1980 to 2022. Source: (Pielke, Jr. 2024)

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. Finally, the U.S. economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period, though not in the continental U.S. (Chapter 6), and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes typically stems from hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 2024). Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini *et al.* 2015, Lee and Dessler 2023). The U.S. EPA (citing data from the Centers for Disease Control) reports that on average over 1999 to 2015 there were 2.2 deaths per million Americans for which cold was listed as the main underlying cause and an additional 2.4 deaths per million for which cold was listed as a contributing factor (EPA 2025). By contrast there were 1.3 deaths per million for which heat was the main cause and an additional 0.8 per million for which it was a contributor. By this metric cold accounts for approximately double the weather-related deaths as does heat.

Epidemiological methods that consider correlational evidence, not just death certificate reports, indicate the cold/warm ratio might be much higher. A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7 percent of deaths were attributable to sub-optimal temperatures, of which 7.4 percent were attributable to cold and only 0.4 percent were attributable to heat (Gasparini *et al.* 2015). In other words, cold weather killed 18.5 times as many people as did hot weather.

Figure 10.2 shows the distribution of results from Gasparini *et al.* (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9 percent, of which 5.5 percent was due to cold, thus cold weather killed 14 times as many people as hot weather.

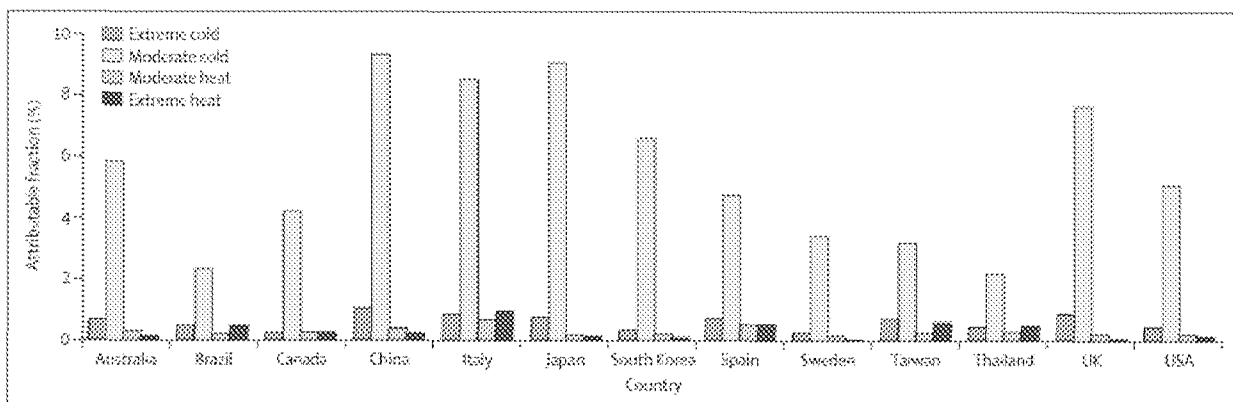


Figure 10.2. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini *et al.* (2015).

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86 percent of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis *et al.* (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb *et al.* (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60 percent decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million

deaths in 211 U.S. cities from 1962 to 2006. Nordio *et al.* (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, rising temperatures are associated with a net saving of lives since they reduce mortality from cold events. The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill *et al.* 2022) acknowledges that heat-related mortality risk is declining over time:

Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.

Yet the IPCC misrepresents the overall situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

The observed decline in U.S. heat-related mortality has been specifically attributed to adaptation. Wang *et al.* (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live. Wang *et al.* (2018) project not only no increase in heat-related mortality, but an overall mortality *decrease* for the U.S. as a whole. They conclude that

Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.

10.3.2 Mortality risks and energy costs

A 2016 study of U.S. long term mortality risks associated with temperature variations (Barreca *et al.* 2016) showed that increases in mortality across the U.S. are associated with both cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus *et al.* (2022) showed that wealthy and poor households in the U.S. adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income

households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

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11 CLIMATE CHANGE, THE ECONOMY, AND THE SOCIAL COST OF CARBON

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in AR5. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy and that trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries, but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points does not justify major revisions to SCC estimates.

11.1 Climate change and economic growth

11.1.1 Overview

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus, 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects of climate change on U.S. economic activity would be small relative to the many other changes that would happen (Schelling 1992).

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report (Arent *et al.* 2014, emphasis added)

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

Evidence since AR5 does not change this assessment. Mohaddes *et al.* (2023) found that warm weather shocks have small negative effects on U.S. state-level output but not income, while cold weather shocks negatively affect both and the impacts are about four times larger, implying a shift to warmer conditions would, if anything, yield a net economic benefit for the U.S.

These statements are validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty.

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen, 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr , 2018, 2020) as have mortality risks (Formetta and Feyen, 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick, 2015). Nor have past extreme weather events had a significant effect on U.S. banks' performance (Blickle *et al.*, 2021); warming has even been shown to be beneficial for the finance and insurance sector (Mohaddes *et al.* 2023). Figure 11.1 below is illustrative. For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it (Storm 2017):

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

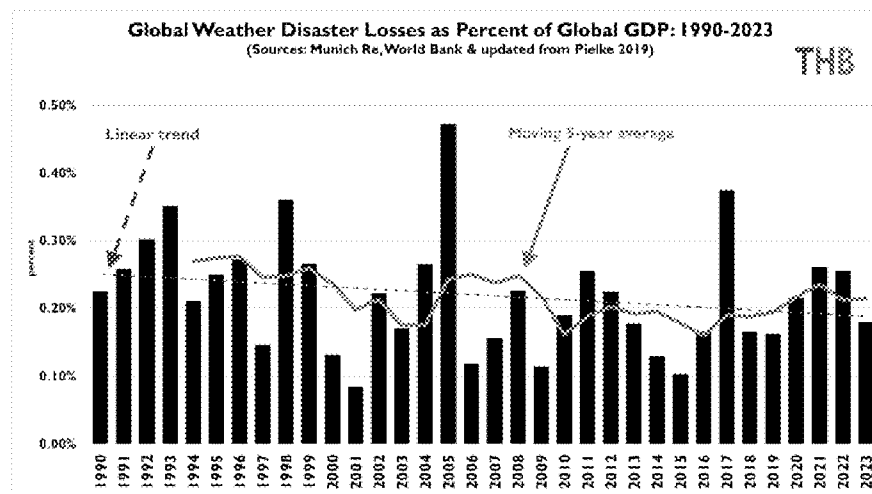


Figure 11.1 Global weather losses as a fraction of GDP. Source: Pielke Jr. (2023)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future, 2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus, 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus' Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we modestly scale back fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even more costly.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

11.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell *et al.* (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke *et al.* (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao *et al.* (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer *et al.* (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang *et al.* (2023) updated the DJO12 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell *et al.* (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke *et al.* (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke *et al.* (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95 percent confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans –86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is considered the original temperature effects reported by Dell *et al.* became small and insignificant.

Berg *et al.* (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall, they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100, even using the extreme RCP8.5 scenario, they computed the average global GDP loss would be only 1.9 percent compared to a scenario with no warming. That is, instead of the economy growing 400 percent it would grow 392%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 392 percent growth.

To summarize, economists consider climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust (Tol 2024). Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

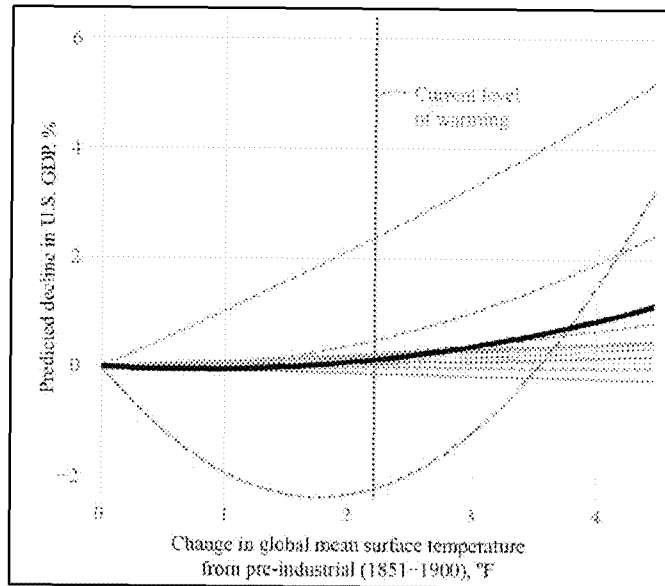


Figure 11.2: Decline in U.S. GDP per degree of warming. Source: CEA-OMB (2023)

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. Figure 11.2, from a 2023 CEA-OMB report, shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe on the U.S. GDP is indeed negligible.

11.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

11.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many, if not most, of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with a changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordhaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0 percent GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5 percent for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this might fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013)

yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

11.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC's guidance. The most recent data-driven ECS values tend to be lower than this (see Chapter 4). Dayaratna *et al.* (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 9) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg *et al.* 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the U.S. Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore *et al.* (2017). But as discussed in Chapter 9, McKittrick (2025) showed that Moore *et al.* (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

11.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 9 looked at climate change and U.S. agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. Haverd *et al.* (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna *et al.* (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF⁴ value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle, 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

11.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz *et al.*, 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example, an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford, 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example, a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen *et al.* 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford, 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to

⁴ Marginal Cost of Public Funds: the optimal carbon tax rate is the SCC divided by the MCPF (Sandmo 1977).

sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth's climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the second type is a possibility. Kypke *et al.* (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon, 2023).

The possible existence of bifurcations in the Earth's climate system implies abrupt transitions are possible, not just in response to large forcing but also to small perturbations. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos *et al.*, 2024) and indeed might not be able to since one implication of the “butterfly effect” is the existence of predictability boundaries of nonlinear systems (Palmer *et al.*, 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict it or prevent it from happening.

AR6 (WGI, Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the “tipping point” concept in discussions of climate change (see <https://report-2023.global-tipping-points.org/what-is-a-tipping-point/> for example). As summarized by AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton *et al.*, 2023). It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate “tipping point” is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of parts of the Greenland and West Antarctic ice sheets. These impacts can reverse on the decadal and century timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). AR6 WG1 Summary for Policy Makers states:

The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is *high confidence* in the 21st century decline, there is only *low*

confidence in the magnitude of the trend. There is *medium confidence* that there will not be an abrupt collapse before 2100. (C.3.4)

There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5). (B.5.2)

For the purpose of SCC calculations, the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz *et al.* incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However, the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there might be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been considered, the result is only a modest increase in the SCC value in the 21st century.

11.2.5 Are there alternatives?

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung, 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However, the uncertainty of SCC estimates doesn't mean that other regulatory measures are inherently better or more efficient. Many emissions regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) cost far more per tonne of abatement than any mainstream SCC estimate, which is sufficient to establish that they fail a cost-benefit test.

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12 GLOBAL CLIMATE IMPACTS OF U.S. EMISSIONS POLICIES

Chapter Summary

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

12.1 The scale problem

The emissions rates and atmospheric concentrations of criteria air contaminants are closely connected because their lifetimes are short and their concentrations are small; when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since emissions mix globally and the global carbon cycle is vast and slow. Any change in local CO₂ emissions today will have only a very small global effect, and only with a long delay.

Following the emission of a pulse (release) of CO₂ into the atmosphere only about 40 ± 15 percent of the extra CO₂ will have been sequestered after twenty years. That fraction rises to 75 ± 10 percent after a thousand years, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais *et al.*, 2013, pp. 472-473). Consequently, any reduction in U.S. emissions would only modestly slow, but not prevent, the rise of global CO₂ concentration. And even if global emissions were to stop tomorrow, it would take decades or centuries to see a meaningful reduction in the global CO₂ concentration and hence human influences on the climate.

Reducing the atmospheric stock of CO₂ would require emissions to fall below the natural sequestration rate, assuming the entire increase is anthropogenic. Since that rate has been averaging about 50 percent of emissions in recent decades, a reduction of global emissions by 50 percent would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy was too difficult for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley, 1998). Lomborg (2016) estimated that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions will have negligible local effects, and only with a long delay. The practice of referring to unilateral U.S. reductions as “combatting climate change” or “taking action on climate” therefore reflects a profound misunderstanding of the scale of the issue.

12.2 Case study: U.S. motor vehicle emissions

The scale problem can be illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. The 2009 Endangerment Finding therefore obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the U.S. public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing U.S. vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to the reduction in global emissions, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0 percent of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating *all* U.S. vehicle-based emissions would retard the accumulation of CO₂ in the atmosphere by a year or two over a century.

It would also reduce the overall warming trend by at most about 3 percent. For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends are determined to a precision of about ± 15 percent, so the impact of reducing the rate of global warming by eliminating U.S. vehicle CO₂ emissions would be far below the limits of measurability. Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, in contrast to the case of local air contaminants like particulates and ozone, even the most aggressive regulatory actions on GHG emissions from U.S. vehicles cannot be expected to remediate alleged climate dangers to the U.S. public on any measurable scale.

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GLOSSARY

2XCO2: Doubling of the atmospheric carbon dioxide (CO₂), a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50 percent of the way to 2XCO₂ compared to 1800.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

ACRIM (Active Cavity Radiometer Irradiance Monitor) GAP: the gap in total solar irradiance data between 1989 and 1991 caused by a delay in the launch of a satellite-borne monitor in time to overlap and intercalibrate with the prior system.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The “opposite” of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

AMO: Atlantic Multidecadal Oscillation, a 60-year cycle of sea surface temperatures in the North Atlantic.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science and the others concerned with societal impacts and mitigation strategies. The most recent was AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CLIMATE CHANGE: A change in climate due to human influences, as opposed to climate variability which is natural in origin.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyze economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens of a country, including exports and imports, usually over one year.

GDP (Gross National Product): Total market value of all the domestically-produced final goods and services produced by the citizens of a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PDO: Pacific Decadal Oscillation, a recurring ocean-atmosphere interaction centered over the Pacific basin associated with predominantly warm or cool patterns that influence the global climate.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TONNE: Metric ton.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

TSI (Total Solar Irradiance): The measure of the total amount of incident solar radiation per unit area, including all wavelengths of electromagnetic radiation, that reaches the Earth's atmosphere. Typically shown in units of watts per square meter (W/m²).

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

METADATA FOR FIGURES AND TABLES

Figure 2.1 Screen shot from Figure 3 of Zhu *et al.* 2016 <https://www.nature.com/articles/nclimate3004>

Figure 2.2 Data replotted from Berner 2006 Figure 18, with annotation in red added by authors
<https://www.sciencedirect.com/science/article/pii/S0016703706002031>

Figure 2.3 Screen shot from Gerhart and Ward (2010) Figure 2
<https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>

Figure 2.4 Screenshot from Copernicus Marine Services
https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description

Figure 2.5 Screen shot from AIMS (2023) Figures 2-4
https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf

Figure 3.1.1 Screen shot of AR6 WG1 Ch2 Fig 10

Figure 3.1.2 Screen shot of AR6 WG1 Ch7 Fig 7-6

Figure 3.1.3 Author created figure. CO2 data source: <https://gml.noaa.gov/ccgg/trends/index.html>

Figure 3.2.1 Screen shot from Hausfather *et al.* (2019) Figure S4 <https://doi.org/10.1029/2019GL085378>

Figure 3.2.2 Author created figure. Data source: Freidlingstein *et al.* (2024)
<https://essd.copernicus.org/preprints/essd-2024-519>
Data source: <https://globalcarbonbudget.org/download/1442/>

Figure 3.2.3 Author-created using OLS trends, Data source:
<https://globalcarbonbudget.org/download/1442/>

Figure 3.2.4 Author-created using OLS trends, Data source:
<https://globalcarbonbudget.org/download/1442/>

Figure 4.1 Screen shot from Scafetta (2021) Figure 1 <https://doi.org/10.3390/cli9110161>

Figure 5.1 Data source: <https://climexp.knmi.nl/start.cgi>. Author-created figure. One ensemble member per model, yearly average temperatures are computed from the global monthly raw temperatures; ‘range’ is the warmest model temperature minus the coolest model temperature in each year; standard deviation computed across all 33 models’ raw temperatures in each year.

Figure 5.2 Screen shot from Scafetta (2023) Figure 2
<https://doi.org/10.1007/s00382-022-06493-w>

Figure 5.3 Author created figure. Data source: <https://climexp.knmi.nl/start.cgi>. One SSP370 ensemble member per model. Linear OLS trends computed from global monthly temperature anomalies relative to 1981-2010.

Figure 5.4 Author created figure, based on Figure 3 of McKittrick and Christy (2020)

<https://doi.org/10.1029/2020EA001281>. Updated using same methods and data extended from 2014 to 2024, see McKittrick and Christy (2025) in chapter references.

Figure 5.6 Screen shot of IPCC AR5 Figure 10.SM1, with author annotations

Figure 5.7 Author created figure following Christy and McNider (2017) <https://doi.org/10.1007/s13143-017-0070-z> with updated data available at https://www.nsstc.uah.edu/data/cmip6/ERA5_REANALYSES/ and https://www.nsstc.uah.edu/data/cmip6/JRA3Q_REANALYSES/ compiled here https://www.nsstc.uah.edu/data/cmip6/CWG25_Fig_5.7_Table_250627.xlsx

Figure 5.8 Screen shot from https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (accessed May 27, 2025)

Figure 5.9 Screen shot from Rugenstein and Hakuba (2023) Figure 1 <https://doi.org/10.1029/2022GL101802>

Figure 5.10 Author created figure. Data source <https://climexp.knmi.nl/start.cgi>. OLS linear trends. One SSP370 ensemble member per model, averaged surface air temperatures for June through August over 31N to 49N latitude, 84W to 102W longitude. Observed temperature data for same months from NOAA/NCEI at <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series> for the 12 Corn Belt states averaged together.

Figure 6.1.1 Author replot of Figure 10 from Koutsoyiannis (2013) <http://dx.doi.org/10.1080/02626667.2013.804626>

Figure 6.2.1 Screen shot of figure from Maue (2025) <https://climatlas.com/tropical/>

Figure 6.2.2 Author created figure. Data from National Hurricane Center (2024) <https://www.nhc.noaa.gov/climo/>

Figure 6.2.3 Author created figure. Data from NOAA HRD https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html

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Figure 6.3.1 Screen shot from NCA4 Figure 6.4

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Figure 6.8.1 Screen shot from Lizundia-Loiola *et al.* (2021) Figure 12.

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<https://www.pnas.org/doi/pdf/10.1073/pnas.1112839109>

Figure 6.8.3 Author created Figure. Data 1926 to 2016:
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Impacts of Carbon Dioxide Emissions on the U.S. Climate

Climate Working Group
United States Department of Energy
July 15, 2025

Impacts of Carbon Dioxide Emissions on the U.S. Climate

Report to U.S. Energy Secretary Christopher Wright

July 15, 2025

Climate Working Group:

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SECRETARY'S FOREWORD

Energy, Integrity, and the Power of Human Potential

Over my lifetime, I've had the privilege of working as an energy entrepreneur across a range of fields—nuclear, geothermal, natural gas, and more—and I now serve as Secretary of Energy under President Donald Trump. But above all, I'm a physical scientist who sees modern energy as nothing short of miraculous. It powers every aspect of modern life, drives every industry, and has made America an energy powerhouse with the ability to fuel global progress.

The rise of human flourishing over the past two centuries is a story worth celebrating. Yet we are told—relentlessly—that the very energy systems that enabled this progress now pose an existential threat. Hydrocarbon-based fuels, the argument goes, must be rapidly abandoned or else we risk planetary ruin.

That view demands scrutiny. That's why I commissioned this report: to encourage a more thoughtful and science-based conversation about climate change and energy. With my technical background, I've reviewed reports from the Intergovernmental Panel on Climate Change, the U.S. government's assessments, and the academic literature. I've also engaged with many climate scientists, including the authors of this report.

What I've found is that media coverage often distorts the science. Many people—even well-meaning ones—walk away with a view of climate change that is exaggerated or incomplete. To provide clarity, I asked a diverse team of independent experts to summarize the current state of climate science, with a focus on how it relates to the United States.

I didn't select these authors because we always agree—far from it. In fact, they may not always agree with each other. But I chose them for their rigor, honesty, and willingness to elevate the debate. I exerted no control over their conclusions. What you'll read are their words, drawn from the best available data and scientific assessments.

I've reviewed the report carefully and challenged its findings. I believe it faithfully represents the state of climate science today. Still, many readers may be surprised by its conclusions—which differ in important ways from the mainstream narrative. That's a sign of how far the public conversation has drifted from the science itself.

To correct course, we need open, respectful, and informed debate. That's why I'm inviting public comment on this report. Honest scrutiny and scientific transparency should be at the heart of our policymaking.

Climate change is real, and it deserves attention. But it is not the greatest threat facing humanity. That distinction belongs to global energy poverty. As someone who values data, I know that improving the human condition depends on expanding access to reliable, affordable energy. Climate change is a challenge—not a catastrophe. But misguided policies based on fear rather than facts could truly endanger human well-being.

We stand at the threshold of a new era of energy leadership. If we empower innovation rather than restrain it, America can lead the world in providing cleaner, more abundant energy—lifting billions out of poverty, strengthening our economy, and improving our environment along the way.

EXECUTIVE SUMMARY

This report reviews scientific certainties and uncertainties in how anthropogenic carbon dioxide (CO₂) emissions have affected, or will affect, the Nation's climate, extreme weather events, and selected metrics of societal well-being. Those emissions are increasing the concentration of CO₂ in the atmosphere through a complex and variable carbon cycle, where some portion of the additional CO₂ persists in the atmosphere for centuries.

Elevated concentrations of CO₂ directly enhance plant growth, globally “greening” the planet and increasing agricultural productivity. They also make the oceans less alkaline (lower the pH) by an amount within the range of natural variability. That is possibly detrimental to coral reefs, although the recent rebound of the Great Barrier Reef suggests otherwise.

Carbon dioxide also acts as a greenhouse gas, exerting a warming influence on climate and weather. Scenarios of future CO₂ emissions have tended to overestimate observed levels.

The world's several dozen detailed climate models offer little guidance on how the climate responds to elevated CO₂, with the average surface warming under a doubling of the CO₂ concentration ranging from 1.8°C to 5.7°C, a larger range than data driven estimates that suggest a response in the range 1.8°C to 2.7°C.

Detailed climate models generally run “hot” in their description of the climate of the past few decades - too much warming at the surface and too much amplification of warming in the lower- and mid-troposphere. They also produce too much stratospheric cooling, too much snow loss, and too much warming in the U.S. Corn Belt. The combination of overly sensitive models and extreme scenarios for future emissions has exaggerated projections of future warming.

Most extreme weather events do not show long-term trends. Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data. Additionally, forest management practices are often overlooked in assessing wildfire activity. Global sea level has risen approximately 8 inches since 1900, but there are significant regional variations in tide gauge data driven primarily by local land subsidence; U.S. tide gauge measurements in aggregate show no obvious acceleration in sea level rise beyond the historical average rate.

The attribution of particular climate changes or extreme weather events to human CO₂ emissions is challenged by natural climate variability, data limitations, and inherent model deficiencies. Moreover, solar activity's contribution to the late 20th century warming might be underestimated.

Both models and experience suggest that CO₂-induced warming might be less damaging economically than commonly believed, and excessively aggressive mitigation policies could prove more detrimental than beneficial. Social Cost of Carbon estimates, which attempt to quantify the economic damage of CO₂ emissions, are highly sensitive to their underlying assumptions and so provide limited independent information.

The report supports a more nuanced and evidence-based approach for informing climate policy. The risks and benefits of a climate changing under both natural and human influences must be weighed against the costs, efficacy, and collateral impacts of any “climate action”, considering the nation's need for reliable and affordable energy with minimal local pollution. Beyond continuing precise, un-interrupted observations of the global climate system, it will be important to make realistic assumptions about future emissions, re-evaluate climate models to address biases and uncertainties, and clearly acknowledge the limitations of extreme event attribution studies. An approach that acknowledges both the potential risks and benefits of CO₂, rather than relying on flawed models and extreme scenarios, is essential for informed and effective decision-making.

PREFACE

This document originated in late March 2025 when Secretary Wright assembled an independent group to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the U.S. public. We agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The group began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. Rather, we chose to focus on topics that are treated by a serious, established academic literature; that are relevant to our charge; that are downplayed in, or absent from, recent assessment reports; and that are within our competence.

While the report is intended to be accessible to non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics covered. We have focused as much as possible on literature published since 2020 and referenced previous IPCC and NCA assessment reports. We have also used data through 2024 where possible.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support of independent scientific assessment and open scientific debate.

John Christy, Ph.D.

Judith Curry, Ph.D.

Steven Koonin, Ph.D.

Ross McKittrick, Ph.D.

Roy Spencer, Ph.D.

PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE CLIMATE

1 CARBON DIOXIDE AS A POLLUTANT

Chapter summary:

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Pollutants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

The Clean Air Act of 1970 defined six so-called Criteria Air Contaminants subject to regulation (EPA): particulate matter, ground-level ozone, sulfur dioxide, nitrogen dioxide, lead, and carbon monoxide. In 2007, the Supreme Court ruled that greenhouse gases (CO₂ among them) were also “pollutants” subject to regulation under Clean Air Act (Mass. v. EPA, 2007). While the definition of “pollutant” is ultimately a legal matter, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are beneficial for vegetation. In these aspects, CO₂ is similar to water vapor.

Ambient outdoor air today contains about 430 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The U.S. Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA, 2024). Allen *et al.* (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG) that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

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2 DIRECT IMPACTS OF CO₂ ON THE ENVIRONMENT

Chapter summary:

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water makes the oceans less alkaline. The recent decline in pH is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Decreasing pH might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50 percent of the Earth versus “browning” over only four percent and attributed 70 percent of the greening to rising CO₂ levels (see Figure 2.1).

Zheng *et al.* (2017) confirmed the pattern, noting that greening over thirty years had added 8 percent to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen *et al.* (2019) noted that China and India were exploiting it through land management changes. Thus, while China accounts for only 6.6 percent of global vegetated area it accounts for 25 percent of global net increase in LAI. Piao *et al.* (2020) noted that greening was even observable in the Arctic.

While plant models predict increased photosynthesis in response to rising CO₂, Haverd *et al.* (2020) reported a CO₂ fertilization rate nearly double model predictions. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30 percent since 1900, versus 17 percent predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and agriculture will be discussed in Chapter 9.

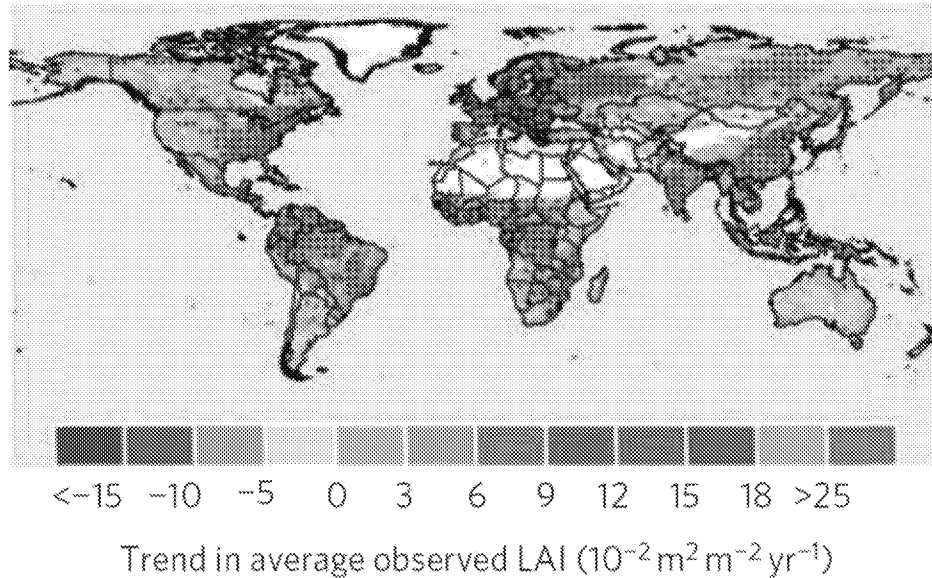


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu *et al.* 2016 Figure 3.

Finally, Chen *et al.* (2024) surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55 percent of the globe while browning was accelerating over only 7 percent. In other words, the greening trend continued with no evidence of slowdown, and CO_2 fertilization remained the dominant driver

2.1.2 Photosynthesis and CO_2 levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO_2 is available at the surface of the Rubisco enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO_2 levels were usually many times higher than they are today, as shown in Figure 2.2.

About 400 million years ago CO_2 levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd *et al.* 2024). Over the past 35 million years the level of atmospheric CO_2 has been steadily declining, falling to as low as 170 ppm during glaciations (Gerhart and Ward 2010).

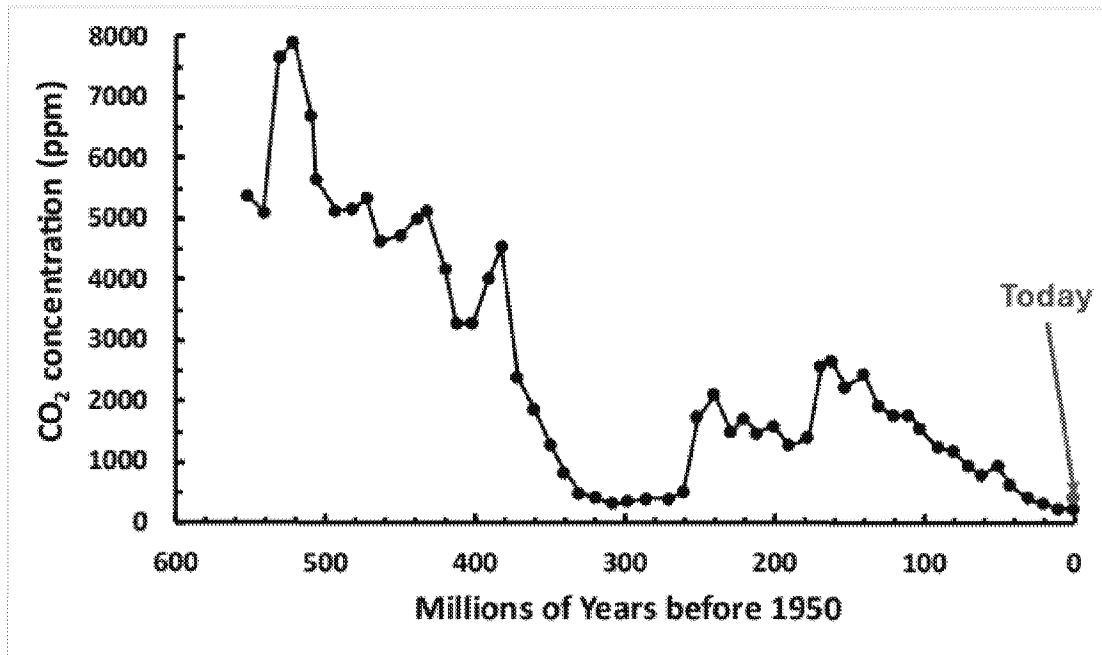


Figure 2.2. Ambient CO₂ levels over the past 550 million years. Today's concentration of 430 ppm is also shown. Source: (Berner 2006)

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C₄, in which CO₂ is concentrated in the vicinity of Rubisco, allowing for the C₃ process to function more efficiently. For agricultural purposes the plant categories are:

- C₃: rice, wheat, soybeans and most other crops
- C₄: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth would have declined and eventually ceased. Below 180 ppm, the growth rates of many C₃ species are reduced 40-60 percent relative to 350 ppm (Gerhart and Ward 2010) and growth has stopped altogether under experimental conditions of 60—140 ppm CO₂. Some C₄ plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Current CO₂ levels are about 430 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3, reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains induced by increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

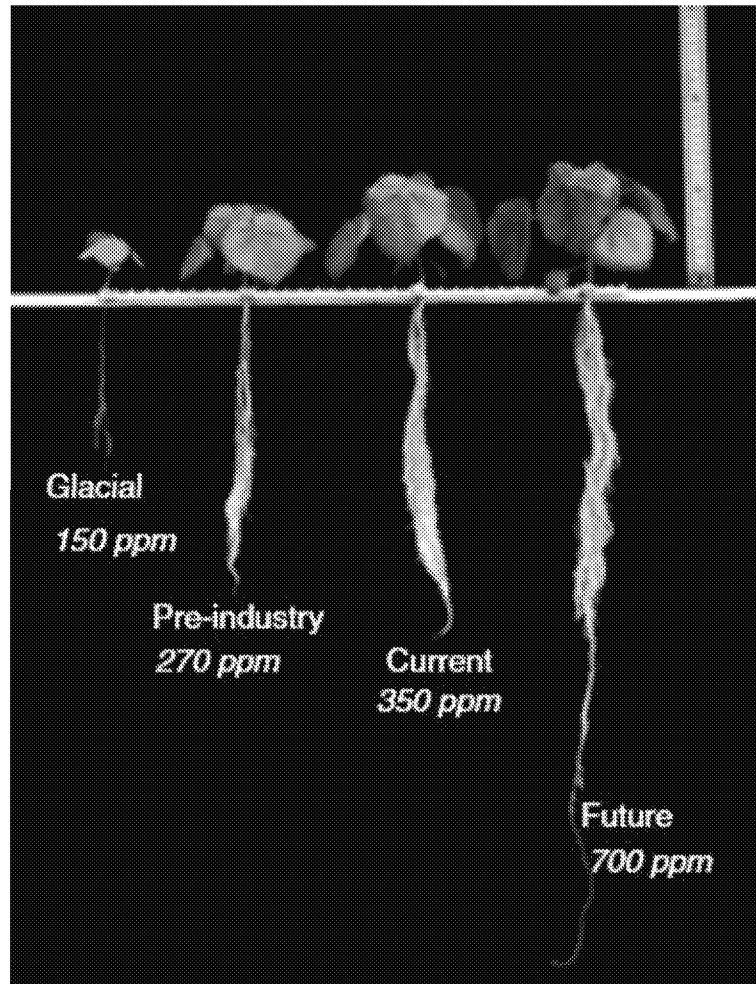


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010). Note “Current” corresponds to 1988 in image.

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, allowing water to evaporate. Under enriched CO₂ conditions the stomata remain closed for longer periods, thus helping the plant retain water longer, and so increasing water use efficiency.

Specific effects of climate change on U.S. agriculture will be reviewed in Chapter 9.

2.1.3 Rising CO₂ and crop water use efficiency

Derying *et al.* (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and to reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 9) on crop yield changes for maize (corn), wheat, rice, and soybean and combined

it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 emissions scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. They reported that models without CO₂ fertilization predicted CWP losses in every region, but those were more than offset by CO₂ fertilization so that all regions showed a net CWP gain. Deryng *et al.* (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90 percent for rice and 60 percent for maize.

Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that global water use by plants had not increased, despite the extra biomass.

Deryng *et al.* (2016) assumed that climate change would “exacerbate water scarcity”. Yet while models do predict that drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang *et al.* (2024) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; at most only 4 percent of currently arid areas will see increased desertification.

2.1.4 CO₂ fertilization benefits in IPCC Reports

The IPCC has only minimally discussed global greening and CO₂ fertilization of agricultural crops. The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report, entitled “global greening and browning,” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries, and Synthesis Reports do not discuss the topic.

2.2 The Alkaline Oceans

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is alkaline (also termed basic) and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increased, the oceans absorbed more, which decreases their pH. Depending upon the oceans’ buffering capacity, they are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

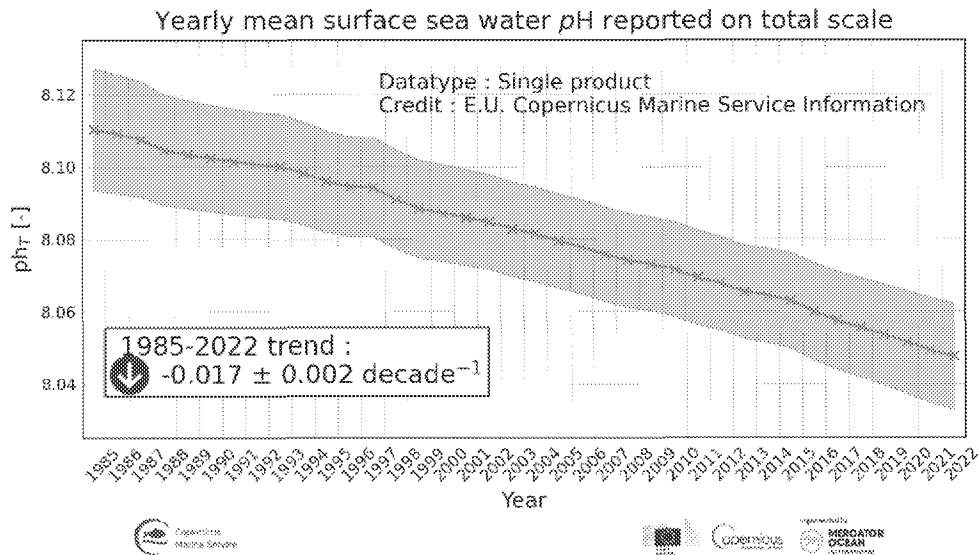


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 to 7.0 (Kriessansen-Totton *et al.*, 2018). On the time scale of thousands of years, boron isotope proxy measurements show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae *et al.*, 2018). Thus, ocean biota appear to be resilient to natural long-term changes in ocean pH since marine organisms were exposed to wide ranges in pH.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath *et al.* (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14 percent decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd *et al.* (2013) showed that report to have resulted from a biased data analysis that, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) to the original study compared to only 11 citations to the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates that coral production has rebounded strongly (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden *et al.*, 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole, 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has surprised some observers.

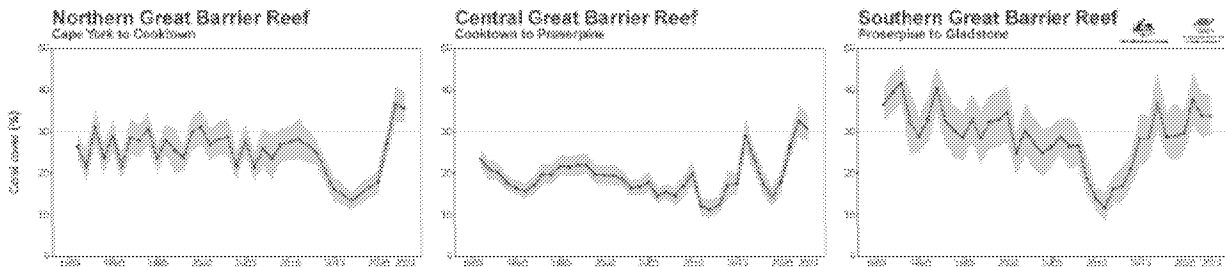


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the reported impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016).

Similarly, a meta-analysis (Clements *et al.*, 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large impacts of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to counter the “decline effect”:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research (Clements *et al.*, 2021).

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. The ancestors of modern coral first appeared about 245 million ago; as can be seen from Figure 2.2, CO₂ levels for more than 200 million years afterward were many times higher than they are today. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

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3 HUMAN INFLUENCES ON THE CLIMATE

Chapter Summary:

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative energy balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. Most academic climate impact studies in recent years are based upon the extreme RCP 8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. While models disagree over the rate of land and ocean CO₂ uptake, all agree that it has been increasing since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean exchange energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the heat it radiates to space. Averaged over the Earth's surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

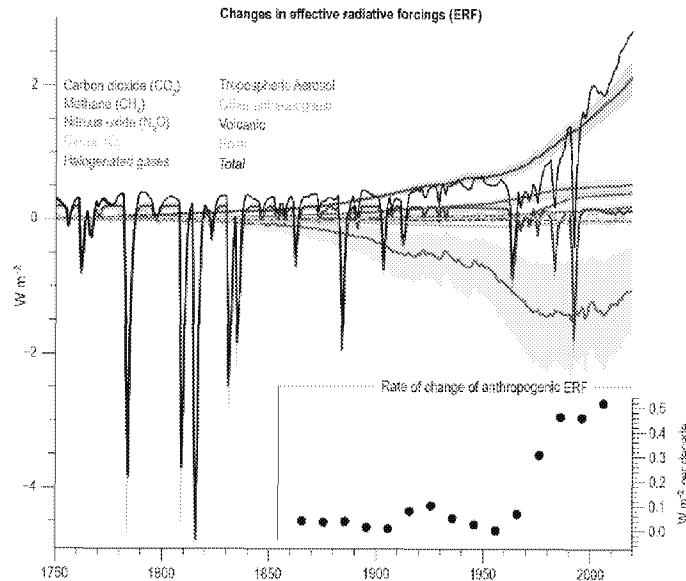


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Shading indicates uncertainty ranges. Source: AR6 WGI Ch2 Fig. 10

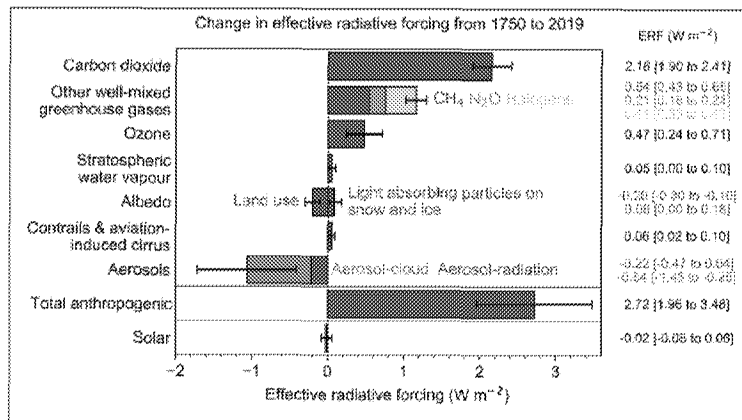


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: AR6 WGI Ch 7 Fig. 7-6.

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of fossil fuel use. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO_2 are accumulating in the atmosphere, as described in the following section, so that the warming influence is growing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75 percent to CO_2 's warming. Aerosols exert an overall cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO_2 , but also the more uncertain cooling effects of aerosols.

The IPCC assesses the change in the radiative forcing by the sun to be negligible, based on their preference for data reconstructions that imply minimal solar change since preindustrial times. But Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature

covering the years 1600-2000; the reconstructions vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. This delay prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta *et al.* 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 hangs on how the ACRIM data gap is filled. Connolly *et al.* (2021) found that the IPCC's consensus statements on solar forcing were formulated prematurely through the suppression of dissenting scientific opinions.

Another natural radiative forcing component is volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins *et al.* 2023, Schoeberl *et al.* 2024).

Figure 3.1.1 shows that the anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m².

Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends on how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii, generally used as the representative global average concentration, is available online at [[HYPERLINK "https://gml.noaa.gov/ccgg/trends/index.html"](https://gml.noaa.gov/ccgg/trends/index.html)]. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2, C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at levels below 100 ppm, so if CO₂ levels had continued falling plant life would have been imperiled.

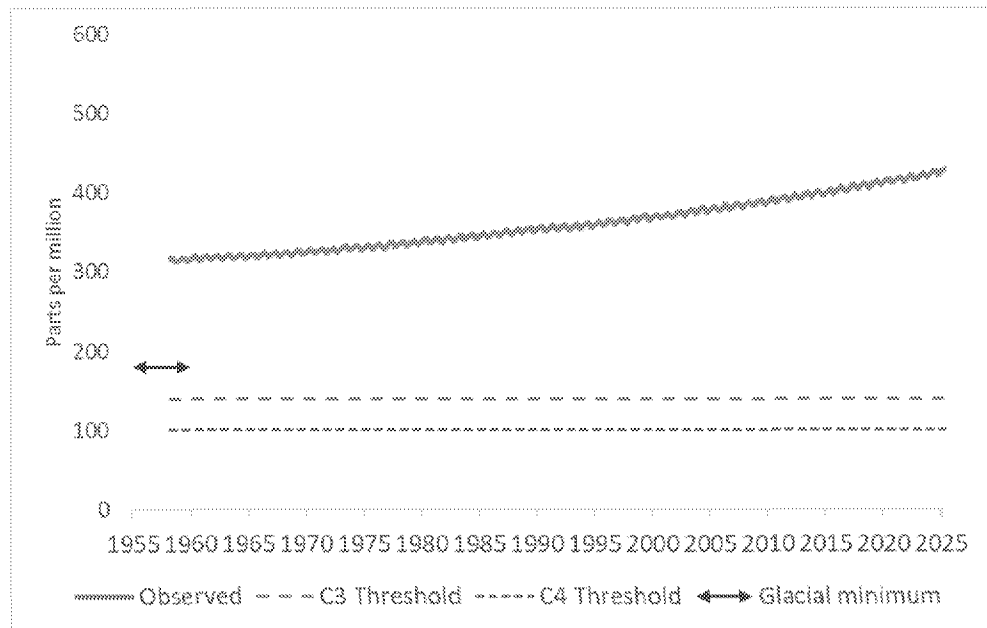


Fig. 3.1.3. Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50 percent of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

The great uncertainties about these many factors make it impossible to precisely predict future emissions. Instead, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show that IPCC emission projections tend to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SRES scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SRES scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges (Figure 3.2.1).

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) describes a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming from 1900 to 2100.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature*, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are unlikely.

Widespread use of RCP8.5 has created a bias towards alarm in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the U.S. National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future outcome.

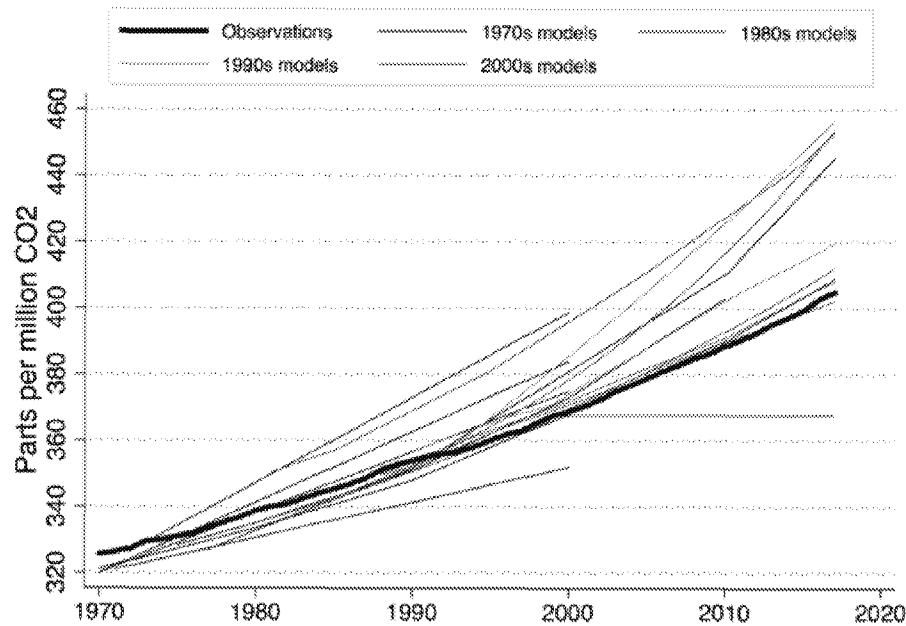


Figure 3.2.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather *et al.* (2019) Figure S4.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.2.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) merged with the emission projection from the IEA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP7.0 and are even below SSP2-4.5.

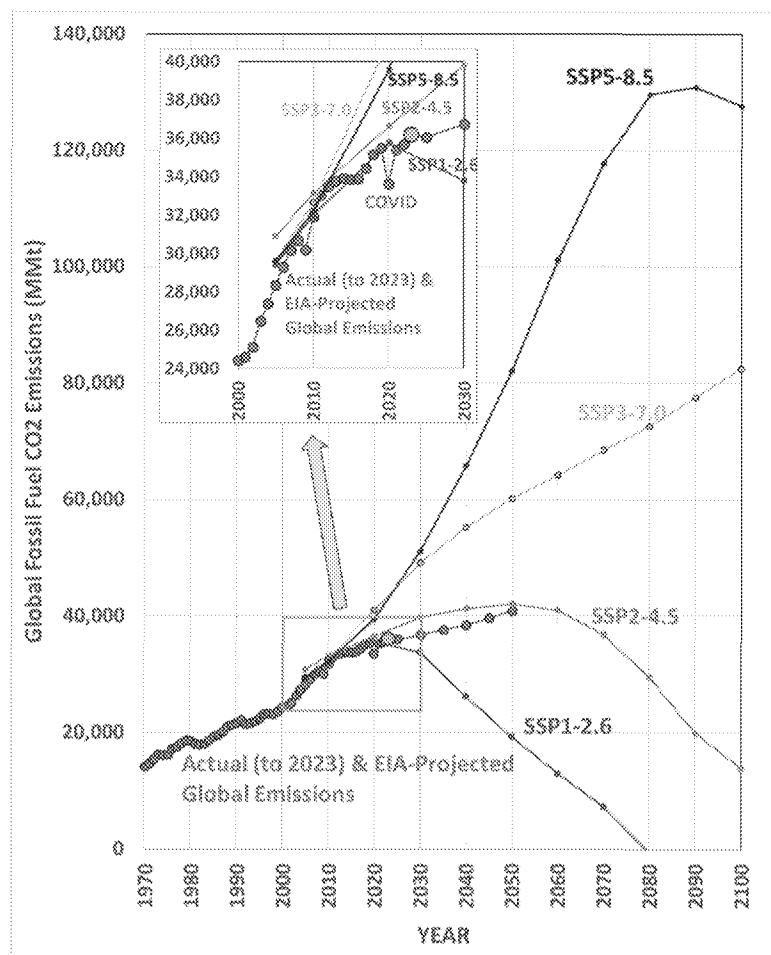


Figure 3.2.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5. Data source: Friedlingstein *et al.* (2024).

3.2.2 The carbon cycle relating emissions and concentrations

Carbon dioxide emissions from fossil fuel burning (and to a lesser extent deforestation and cement production) have led to steadily increasing CO₂ concentrations in the atmosphere, as shown in Fig. 3.1.3. The relation between emissions and concentration is determined by the global carbon cycle of land and ocean processes that exchange carbon with the atmosphere. Our understanding of these processes was reviewed by Crisp *et al.* (2021).

There are about 850 Gt of carbon (GtC) in the Earth's atmosphere², almost all of it in the form of CO₂. Each year, biological processes (plant growth and decay) and physical processes (ocean absorption and outgassing) exchange about 200 GtC of that carbon with the Earth's surface (roughly 80 GtC with the land and 120 GtC with the oceans). Before human activities became significant, removals from the atmosphere were roughly in balance with additions. But burning fossil fuels (coal, oil, and gas) removes carbon from the ground and adds it to the annual exchange with the atmosphere. That addition (together with a much

² Because CO₂ is chemically transformed through the course of the carbon cycle, it is more convenient to track atoms of carbon rather than molecules of CO₂. One gigatonne of carbon (GtC) is equivalent to about 3.7 Gt of CO₂.

smaller contribution from cement manufacturing) amounted to 10.3 GtC in 2023, or only about 5 percent of the annual exchange with the atmosphere.

The carbon cycle accommodates about 50 percent of humanity’s small annual injection of carbon into the air by naturally sequestering it through plant growth and oceanic uptake, while the remainder accumulates in the atmosphere (Ciais *et al.*, 2013). For that reason, the annual increase in atmospheric CO₂ concentration averages only about half of that naively expected from human emissions.

To project future CO₂ concentrations in the atmosphere, and hence future human influences on the climate, it is important to know how the carbon cycle might change in the future. The historical near constancy of that 50 percent fraction means that the more CO₂ humanity has produced, the faster nature removed it from the atmosphere. That 50 percent fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert *et al.*, 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein *et al.*, 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.2.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty in how fast land processes are removing CO₂ from the atmosphere, which in turn creates uncertainty in future atmospheric CO₂ concentrations, which then produce uncertainty in climate model simulations of future climate change.

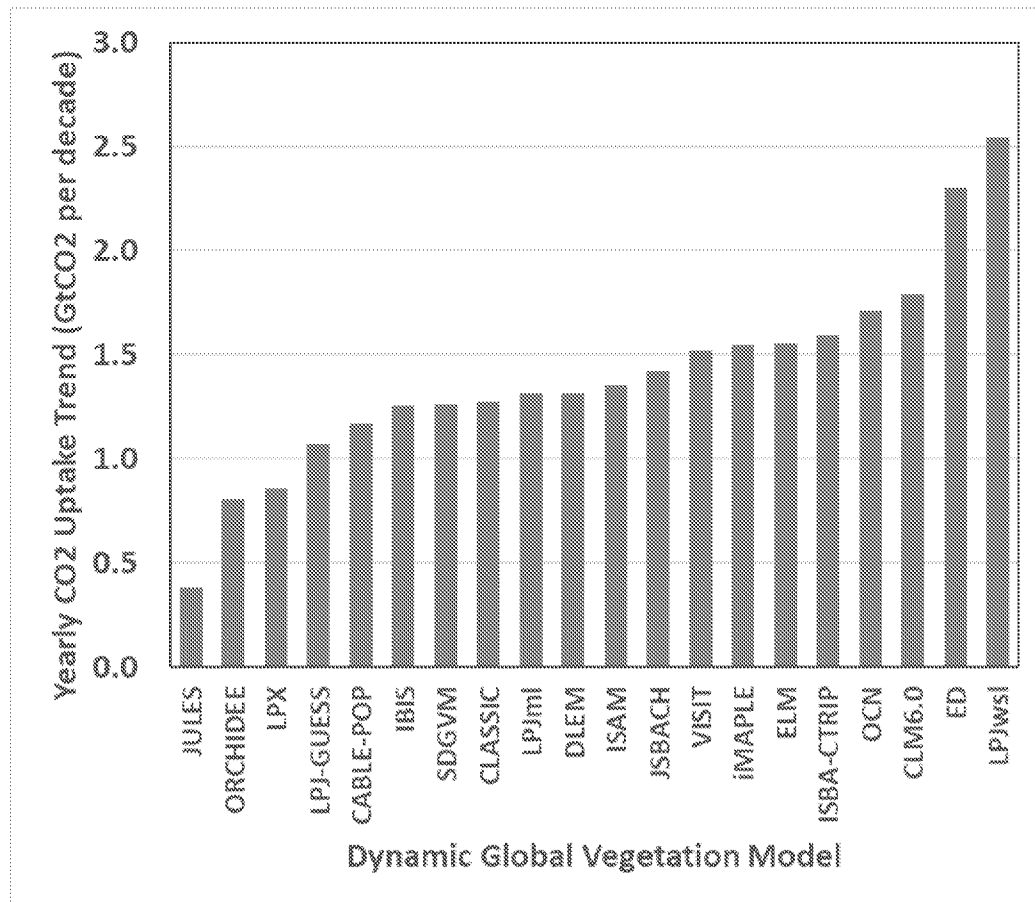


Figure 3.2.3 Trends of annual CO₂ uptake (GtCO₂ per year per decade) by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different ocean biogeochemistry models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.2.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake being only 65 percent faster than the model with the most slowly increasing CO₂ uptake. In spite of the relative agreement among models, Friedlingstein *et al.* (2022) notes that there is substantial discrepancy between the different methods on the strength of the ocean sink over the last decade, particularly in the Southern Ocean.

Note that the average trend in CO₂ uptake across all land models in Fig. 3.2.3 is 25 percent larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

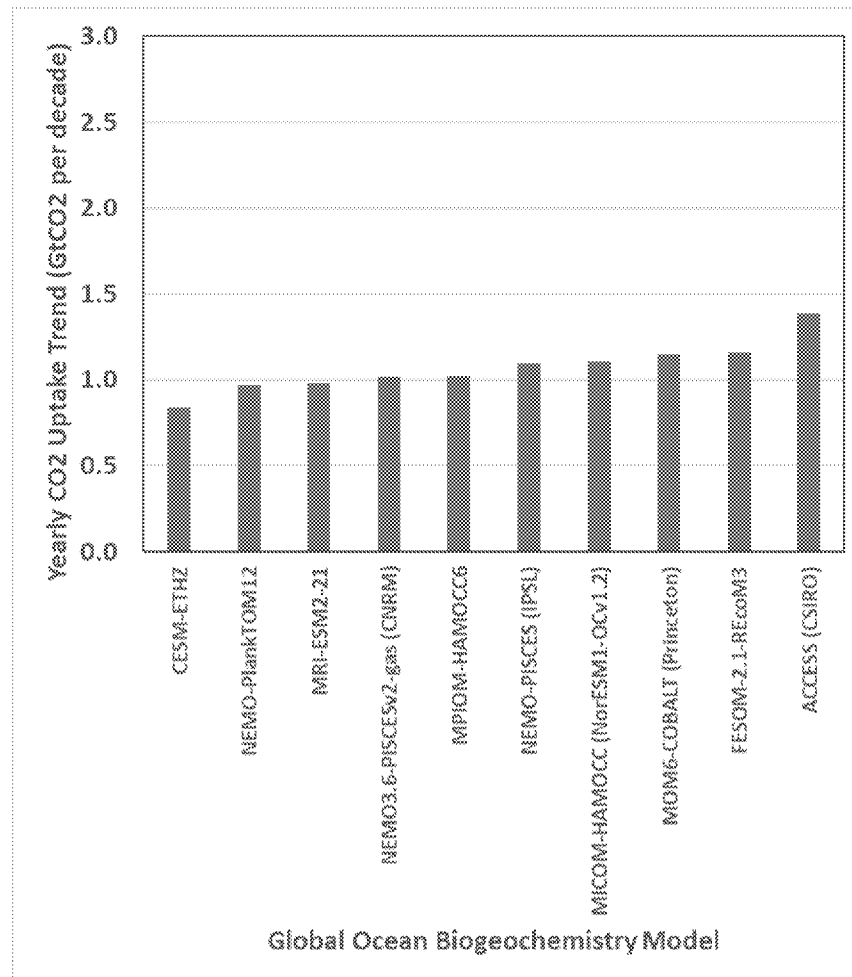


Figure 3.2.4 Trends of annual CO₂ uptake (GtCO₂ per year per decade) by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

3.3 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If these are not removed the data might over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures are sufficient.

AR6 downplayed this issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10 percent in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10 percent upper bound without citing a source. AR4 (WGI p. 244) cited Jones *et al.* (1990) and Peterson *et al.* (1999) as the basis of the claim. Peterson *et al.* had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons while the relative influence of urbanization begins well below that (Spencer *et al.*, 2025). Jones *et al.* compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to

10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10 percent in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10 percent of the observed warming trend.

Several papers appeared in print prior to the IPCC AR4 that argued that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. Their claim was controversial because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. AR5 (p. 189) conceded that AR4 had provided “no explicit evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as already noted, elsewhere in the AR5 report they carried forward AR4 claim that it was less than 10 percent of observed warming. Further they provided no caution about using the land record for climate measurement despite conceding the evidence for UHI contamination. Recently Soon *et al.* (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones *et al.* 1990, Peterson *et al.* 1999, Wickham *et al.* 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic in population, in other words it is strongest at low population density then levels off as local urbanization expands (Oke 1973, Spencer *et al.* 2025). Hence failure to find a difference in warming rates between urban and rural stations does not prove the absence of UHI contamination. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer *et al.* (2025) used newly available historical population archives to undertake such an analysis and found evidence of significant UHI bias in U.S. summertime temperature data.

In summary, while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases have not been completely removed by the data processing algorithms used to produce climate data sets.

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PART II: CLIMATE RESPONSE TO CO₂ EMISSIONS

4 CLIMATE SENSITIVITY TO CO₂ FORCING

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches including historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is less justified; evidence since the AR6 finds the lower bound of the *likely* range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on “climate action.” The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the U.S. National Academy of Sciences (National Research Council 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5–4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and *very unlikely* (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it (Hausfather 2023). Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0–5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna *et al.* 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

By itself, the equilibrium warming effect of a doubling of atmospheric CO₂ is slightly more than 1°C (Soden and Held 2006). Larger values of ECS arise from positive feedbacks that amplify the CO₂ warming. Water vapor feedback is positive: a warmer atmosphere might have more water vapor, which itself is a powerful greenhouse gas. Warmer temperatures also result in less snow and sea ice cover, allowing the

Earth to absorb more of the sun’s radiation. Some simple estimates of these feedbacks increase the ECS to around 2°C (Sherwood *et al.*, 2020). Larger values of ECS are associated with positive cloud feedbacks.

Climate scientists use multiple lines of evidence to determine the Equilibrium Climate Sensitivity:

- Climate model simulations
- Historical observations
- Paleoclimatic reconstructions
- Process understanding of feedbacks

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behavior of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth’s climate sensitivity.

In principle, ECS is an emergent property of GCMs—that is, it is not directly parameterized or tuned, but rather emerges in the results of the simulation. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with an expected warming rate, or aversion to a model’s climate sensitivity being outside an accepted range (Mauritsen *et al.* 2012). This practice was commonplace for the models used in AR4; modelers have moved away from this practice with time. However, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute (MPI) climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by **targeting an ECS of about 3 K using cloud feedbacks**, as opposed to tuning the aerosol forcing.”

In other words, the MPI modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

As noted, direct warming from CO₂ doubling is only about 1°C (Soden and Held 2006); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the need for such long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in AR6 to between 1.8 and 5.7°C (Chen *et al.*, 2021, Scafetta 2021, see Figure 4.1). Far from resolving the model-based climate sensitivity the range appears to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka *et al.*, 2020)

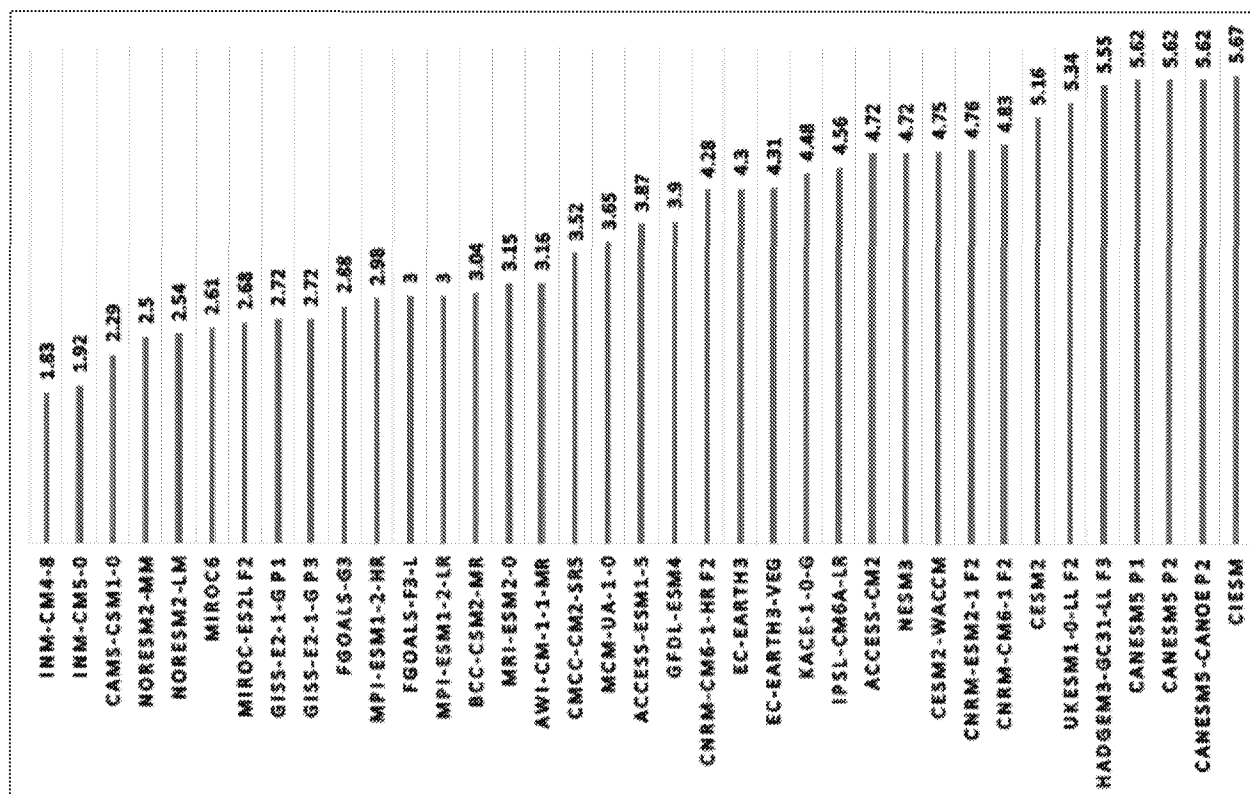


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021)

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6(2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on data-driven methods.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto *et al.*, 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and good data is only available for recent decades. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect; see Figures 3.1.1, 3.1.2). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz *et al.*, 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂.

Paleoclimate proxies are also used to evaluate the sensitivity of past climates by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states might not be applicable to the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For AR6, the IPCC placed primary weight on the results of Sherwood *et al.* (2020) that combined historical data and paleoclimate proxies with the process-based approach and yielded a best estimate of 3.1°C with a *likely* range of 2.6–3.9°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood *et al.* analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood *et al.* and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster *et al.*, 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the west-east temperature gradient, which led the IPCC in AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager *et al.* (2019) pointed out that, contrary to models, the west-east temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee *et al.* (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate might be *lower* than current estimates.

4.4 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the global temperature increase that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (*i.e.*, doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (*e.g.*, ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with AR6 values than was seen in a comparison of the ECS values.

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5 MODELS VERSUS OBSERVATIONS IN THE RECENT PAST

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past several decades. In response to estimated changes in forcing they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, invalid hemispheric albedos, too much snow loss, and too much warming in the Corn Belt. The IPCC has acknowledged some of these issues but not all.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. To assess the fitness of climate models for this purpose, it is reasonable to ask how well they reproduce the current climate and its variations over the past century. The box “Climate modeling” gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, as we discussed in the previous chapter. This range of disagreement among models has not decreased for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends; ability to reproduce the vertical warming profile; and ability to reproduce other climate features such as snowfall. In all cases a persistent finding is that models on average err on the side of too much warming in response to estimated historical forcings.

BOX: Climate modeling

Most climate models, except for the simplest ones, represent Earth's land surface using a grid of squares on the order of 100 km wide. To simulate the atmosphere, typically 30 or more grid boxes are stacked above these squares. The ocean is modeled using a similar but finer grid, resulting in tens of millions of grid boxes for the atmosphere and oceans.

The computer models, based on physical laws, calculate how air, water, and energy move between grid boxes over time. The time step can be as small as 10 minutes, and repeating this process millions of times allows the simulation of climate over centuries. Running these models, even on the most powerful supercomputers, can take months. Comparing simulation results with historical climate data helps assess the accuracy of a model, while projections into the future estimate climate changes under assumed human and natural influences.

Despite sounding straightforward, climate modeling is highly complex. Many critical processes occur at scales smaller than the grid size. For instance, the flows of sunlight and heat in the atmosphere depend strongly on cloud cover. Since tracking individual clouds is impractical, researchers must make “subgrid” assumptions about the distribution of clouds in each grid box. Snow and ice cover, which affects how much sunlight is reflected or absorbed by the surface, is another subgrid factor.

Each subgrid assumption requires numerical parameters, which must be carefully set. Modelers initially estimate these parameters based on physics and observed climate patterns, then run the model. Because early results often diverge significantly from real-world observations, they “tune” these parameters to better match observed climate features. Different modeling teams use distinct assumptions and tuning strategies, leading to varied outcomes. Tuning is a necessary but delicate aspect of climate modeling, as it is for any complex system. Poor tuning can result in inaccurate simulations, while excessive tuning risks artificially steering results toward predetermined conclusions.

The spread of model representations of the current climate is very wide. One of the most basic indicators—Earth's average surface temperature—varies by about 3°C across CMIP6 models prior to 1880 (Figure 5.1), narrows slightly until 2040 then diverges to over 4 °C. For comparison 20th century warming was only about 1.0°C. This variation suggests substantial differences among models' physical processes.

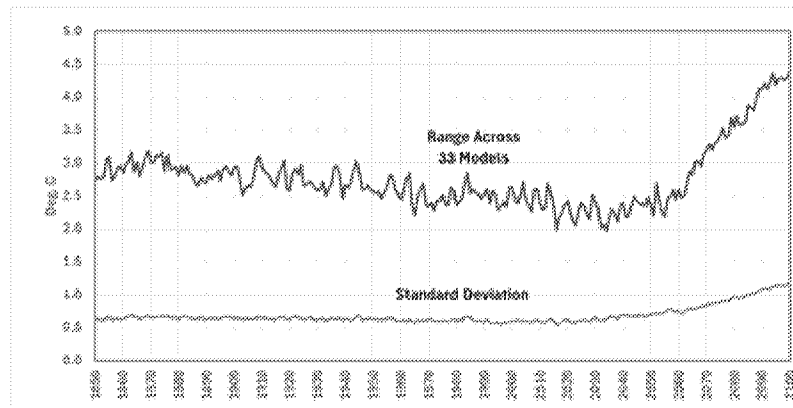


Figure 5.1 CMIP6 Average surface temperature range across 33 models and standard deviation using SSP5-85 scenario. Data from KNMI Climate Explorer website at [[HYPERLINK "https://climexp.knmi.nl/start.cgi"](https://climexp.knmi.nl/start.cgi) \t "_blank"].

Beyond the models' ability to reproduce features of today's climate, the critical issue for society is how well they predict responses to subtle human influences, such as greenhouse gas emissions, aerosol cooling, and land-use changes. The most crucial aspect that models must capture correctly is “feedbacks.” These occur when climate changes either amplify or suppress further warming. In general, the modeled net effect of all feedbacks doubles or triples the direct warming impact of CO₂.

5.2 Surface warming

A straightforward test of a climate model's validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 5.2 is reproduced from Scafetta (2023), that groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

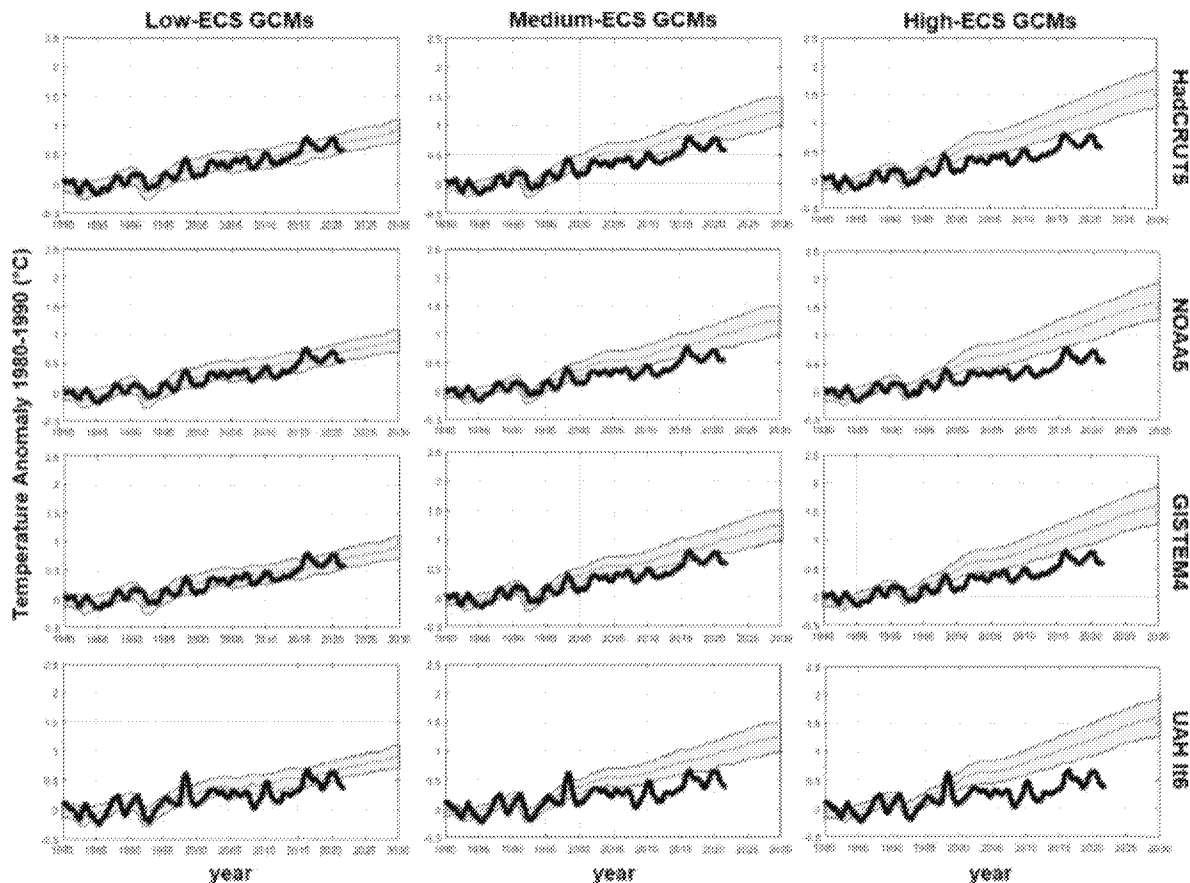


Figure 5.2: Model-Observational comparisons for Earth's surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source. Source: Scafetta (2023) Fig.2.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by comparing trends in surface temperature data products with those in individual climate models, as summarized in Figure 5.3; most climate models show substantially more warming than the observations since 1979.

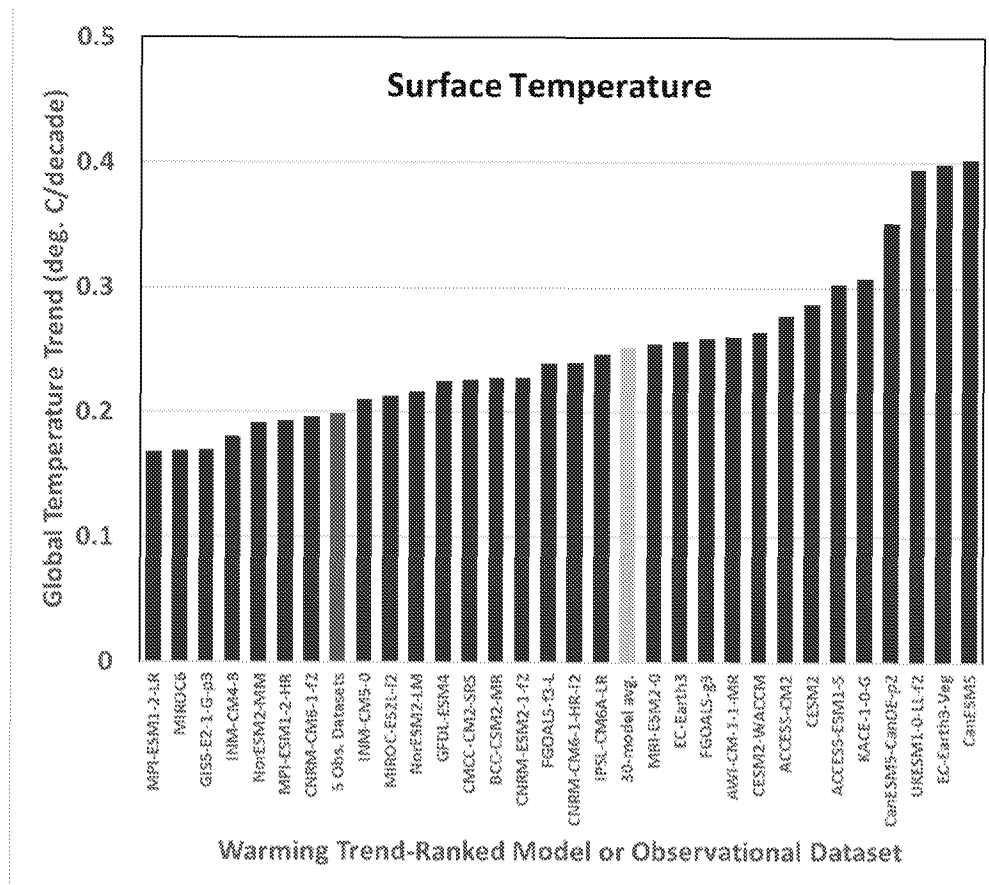


Figure 5.3 Global surface air temperature trends ($^{\circ}\text{C}/\text{decade}$), 1979-2024, from various CMIP6 climate models (red, 30-model average in orange); and the average of three thermometer datasets (HadCRUT5, NOAA Global Temp, and Berkeley 1 deg.) and two reanalysis datasets (ERA5 and NCEP/NCAR R1) in blue. Data source: <https://climexp.knmi.nl/start.cgi>.

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. This region is an important test of climate models since this is where the signal of anthropogenic greenhouse warming emerges first and most strongly. Biases in tropospheric trends indicate model flaws in heat transfer processes that carry over to surface warming biases.

The discrepancy was flagged as a serious inconsistency in the first U.S. Climate Change Science Program report (Karl *et al.* 2006) and has been mentioned in every IPCC report since, but the discrepancy has gotten worse over time, and the bias is now global. McKittrick and Christy (2020) compared tropospheric warming trends in CMIP6 climate models to observed trends from satellites, weather balloons and reanalysis systems. Every model overpredicted the average observed warming trend over 1979-2014 in both Lower- and Mid-Troposphere layers, both globally and in the tropics. In most individual models the bias was statistically significant and on average across models it was highly significant.

Figure 5.4 presents the comparisons with data updated to 2024 (McKittrick and Christy 2025). The recent warm years moved the observed trend up slightly and widened the trend confidence intervals but the overall pattern remains the same: model bias is towards too much warming, in most cases the difference is statistically significant and on average the bias is statistically highly significant. McKittrick and Christy (2020) also showed that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If future climate models were to realistically represent global tropospheric warming, they would likely be less sensitive than even the low-ECS members of the CMIP6 ensemble.

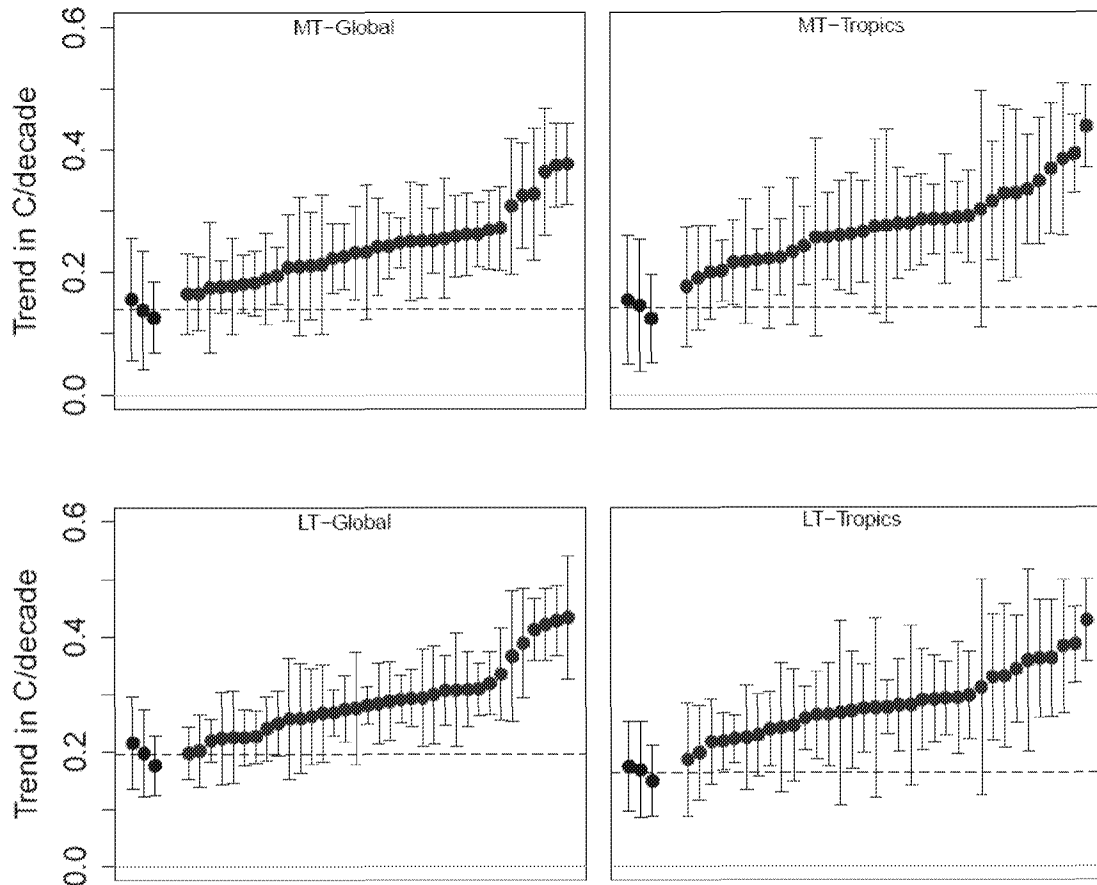


Figure 5.4: Observed versus CMIP6 modeled warming trends (°C/decade 1979-2024) in the global and tropical lower (LT) and mid-troposphere (MT). Uses methodology of McKittrick and Christy (2020) on data updated from 2014 to 2024. Blue dots: warming trends with 95 percent confidence intervals for 3 data products (radiosondes, reanalysis, and satellites). Blue dashed line: warming trend average for 3 observed series. Red dots: modeled warming trends with 95 percent confidence intervals in 35 models arranged lowest to highest.

As mentioned previously, the IPCC has long acknowledged the model-observation mismatch. For example, AR6 pp. 443-444 offers this on the tropical troposphere (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell *et al.*, 2013, 2020; Santer *et al.*, 2017a, b; McKittrick and Christy, 2018; Po-Chedley *et al.*, 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley *et al.*, 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley *et al.*, 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell *et al.*, 2013, 2020; Santer *et al.*, 2017a, b; Suárez-Gutiérrez *et al.*, 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell *et al.*, 2013; Po-Chedley *et al.*, 2021). Hence, we assess with *medium confidence* that CMIP5 and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, despite the accumulation of evidence of excess model warming the IPCC assigns only *medium confidence* to the existence of a warming bias.

5.4 Vertical temperature profile mismatch

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. The comparison was in the IPCC AR5 Chapter 10, although only in the online supplement (Figure 10.SM.1) and only in a figure whose formatting obscured the point. Figure 10.SM.1 is not referenced in the main IPCC report nor in any summary so readers would not have been aware of it. Although not apparent at first glance, it shows that the 1979-2010 warming in the lower troposphere is so small as to be consistent with no GHG forcing at all and is inconsistent with the model runs that do have GHG forcing. In Figure 5.6 we adapt IPCC AR5 Figure 10.SM.1 to draw out this critical point.

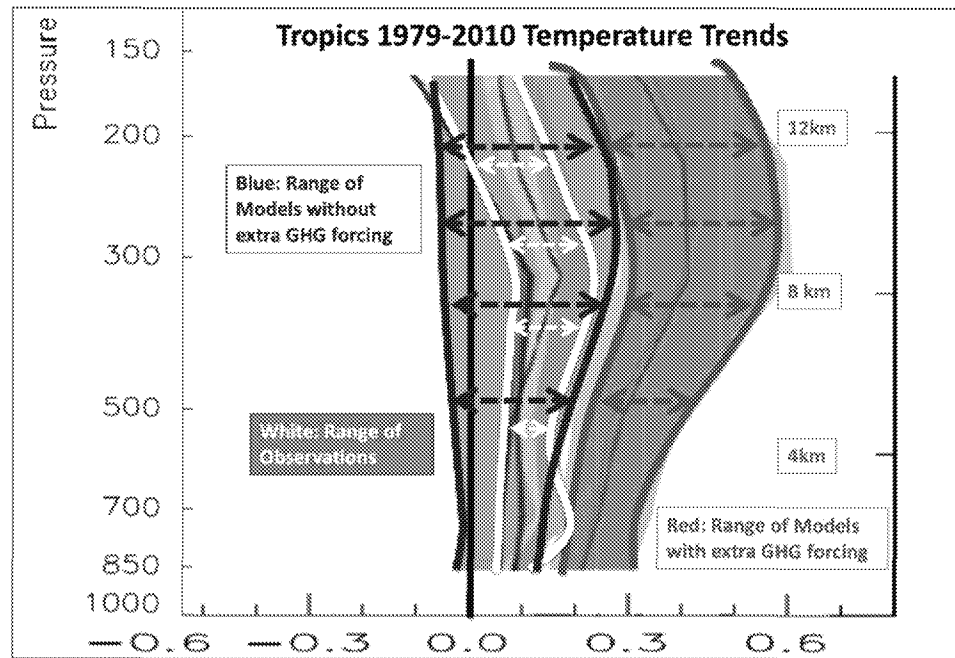


Figure 5.6: Vertical warming pattern for tropics (20S to 20N). Source: Annotated version of IPCC AR5 Figure 10.SM.1

Figure 5.6 compares model and observational temperature trends by altitude between 20S and 20N (the tropics). In this region where the models say the warming should be strongest, the observations (shown here in white) lie within the blue “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the base of the stratosphere, observed warming trends are so small as to be consistent with the output of models that have no anthropogenic CO₂, and inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.7. Modeled temperature trends exceed observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.7 is the tropical tropospheric temperature (TTT) average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again, the observed trends lie below the entire model range.

The wide range of choices made by modelers to characterize the physical processes in the models (see Box: Climate Modeling in Section 5.1 above) is seen by the large spread of trends in the middle troposphere, ± 40 percent about the median (Fig. 5.7). This vividly illustrates the uncertainties in attempts to model (parameterize) a complex system involving turbulence, moist thermodynamics, and energy fluxes over the full range of the tropical atmosphere’s time and space scales.

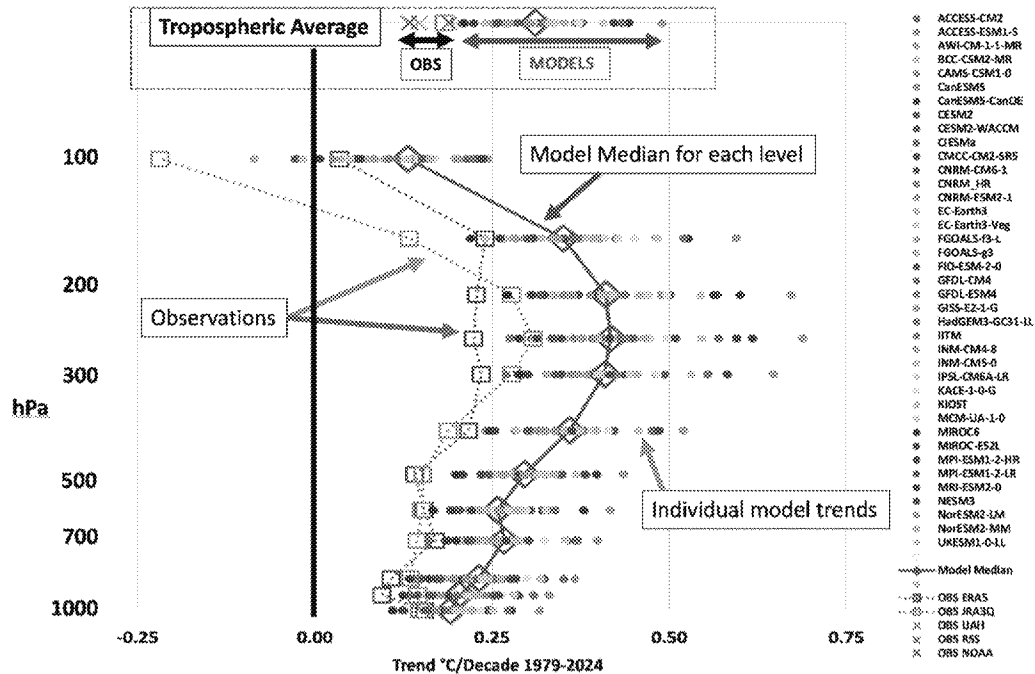


Figure 5.7: Modeled versus observed warming, tropical troposphere. Source: updated from Christy and McNider (2017) including data through 2024. Red line: model average. Green and blue lines: observational series (reanalysis).

This discrepancy has been the source of much controversy, with some arguing that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface (Santer et al. 2008). But there is good evidence that models also exaggerate the amplification rate. Klotzbach *et al.* (2009), showed that models project greater amplification with altitude than is observed. This result was subsequently confirmed by detailed time series analysis (Vogelsang and Nawaz 2016) which found that the model-observational difference is statistically significant.

The atmosphere's temperature profile is a case where models are not merely uncertain but also show a common warming bias relative to observations. This suggests that they misrepresent certain fundamental feedback processes.

The IPCC AR6 did not assess this issue.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. AR6 acknowledged that cooling had been observed but only until the year 2000. The stratosphere has shown some warming since, contrary to model projections.

AR6 WG1 Ch 2 pp. 327-9 states:

Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend,

found by Steiner *et al.* (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona *et al.* (2018) show weak increases over 2000–2015 in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona *et al.* (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.

A combination of tropospheric warming and stratospheric cooling is a commonly cited “fingerprint” of anthropogenic warming. Stratospheric warming since 2000 coincides with continued surface and tropospheric warming, a pattern that is not found in climate model simulations and is not apparently consistent with the anthropogenic fingerprint.

5.6 Snow cover mismatch

Data compiled by the Rutgers University Snow Lab show that Northern Hemisphere winter snow cover is not decreasing (Figure 5.8); if anything, it shows an increasing trend.

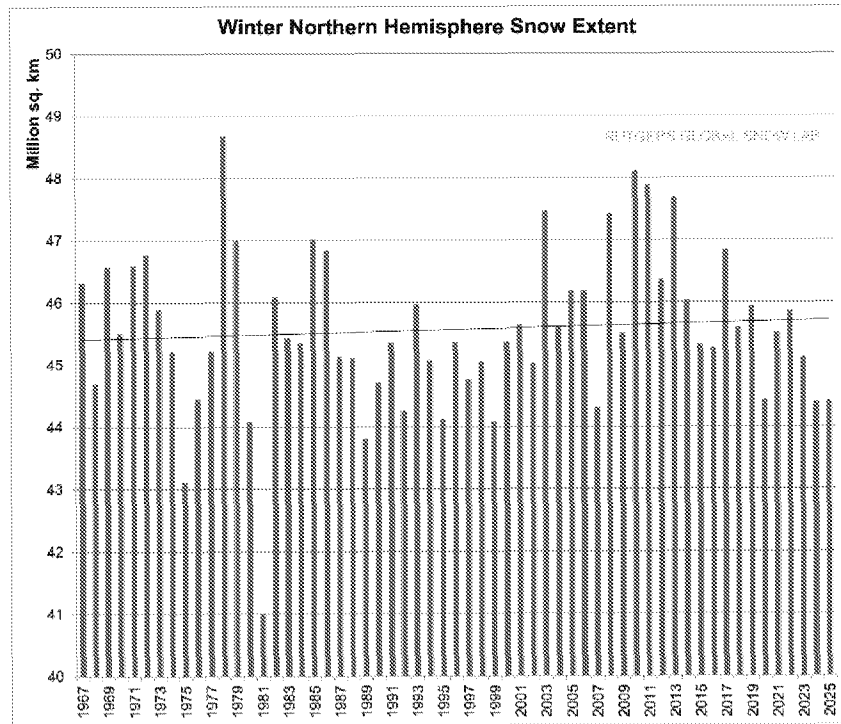


Figure 5.8: Northern Hemisphere Winter Snow extent.

Source: [[HYPERLINK](https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1)]

"https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"]
(accessed May 27, 2025)

Yet models project declining Northern Hemisphere snow cover in a warming climate, as described by Connolly *et al.* (2019).

The climate models were found to poorly explain the observed trends [in Northern Hemisphere snow cover]. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions. Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant.

AR6 largely confines its discussion of changing Northern Hemisphere snow cover extent (SCE) to the Spring season, for which models and observations agree on a downward trend. Regarding Winter changes it remarks as follows (AR6 WGI Ch. 2 p. 344):

Assessment of SCE trends in the NH since 1978 indicates that for the October to February period there is substantial uncertainty in trends with the sign dependent on the observational product. Analysis using the NOAA Climate Data Record shows an increase in October to February SCE (Hernández-Henríquez *et al.*, 2015; Kunkel *et al.*, 2016) while analyses based on satellite borne optical sensors (Hori *et al.*, 2017) or multi-observation products (Mudryk *et al.*, 2020) show a negative trend for all seasons.

AR6 WGI Chapter 9 (p. 1284) points out that the NOAA Climate Data Record showing increased fall and winter SCE is inconsistent with land-based observations and model-based data sets. It notes that using optical satellite imagery to infer SCE in winter is challenging due to cloud cover and decreased solar illumination in winter months. Focusing on the Pacific Coast states (CA, OR and WA) cold season mountain snowfall that melts in spring and summer provides a substantial portion of warm season water resources. A comprehensive reconstruction of snowfall for the main source regions (Cascades and Sierra Nevada Mountains) indicates no significant trends in annual totals since the late 19th century (Christy 2022).

In summary, the up-to-date Rutgers SCE database indicates a mismatch between models and observations. Further work to reconcile conflicting trends in observational data sets is required.

5.7 Hemispheric symmetry of the planetary albedo

The planetary albedo is the fraction of incoming solar radiation reflected by the Earth back to space. It is an important element of the radiative energy balance and influences whether the planet will warm or cool over time. The planetary albedo is typically estimated at around 0.30; variations on the scale of 0.01 correspond to changes in solar forcing of about 3 W/m^2 , an amount larger than current anthropogenic forcing. It has long been noted that models disagree with each other and with observations on the value of the global planetary albedo (Stephens *et al.* 2015).

An intriguing property of the Earth's albedo is that, on average, the Northern Hemisphere (NH) and Southern Hemisphere (SH) have had nearly the same albedo, at least throughout the fifty-year satellite record (Stephens *et al.*, 2015). This symmetry is surprising, because the SH has much more ocean than land. Since ocean is less reflective than land, the NH should have higher albedo. Clouds (which are highly reflective) are more common in the NH and so compensate the surface albedo imbalances of the two hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH. While the mechanism for this hemispheric symmetry is unclear, it likely operates on large temporal and spatial scales.

The hemispheric symmetry of the albedo is a simple gross metric for climate models. Rugenstein and Hakuba (2023) defined that metric as the difference between the NH and SH annual mean albedos, expressed as Wm^{-2} of the reflected sunlight, and compiled it for the CMIP6 climate models, as shown in Figure 5.9. Most of the CMIP6 models do not reproduce the small observed asymmetry (about 0.1 Wm^{-2}) and even disagree as to which hemisphere is more reflective. Moreover, the magnitude of the asymmetry ranges up to 5 Wm^{-2} in some models, twice as large as the current anthropogenic forcing (about 2.5 Wm^{-2}).

The significance of unphysical albedo asymmetries in the climate models is not yet fully known. However, other model studies suggest that interhemispheric changes in albedo can alter poleward heat fluxes, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy between models and observations further raises issues regarding cloud feedback processes and so more generally diminishes confidence in model projections of the future climate.

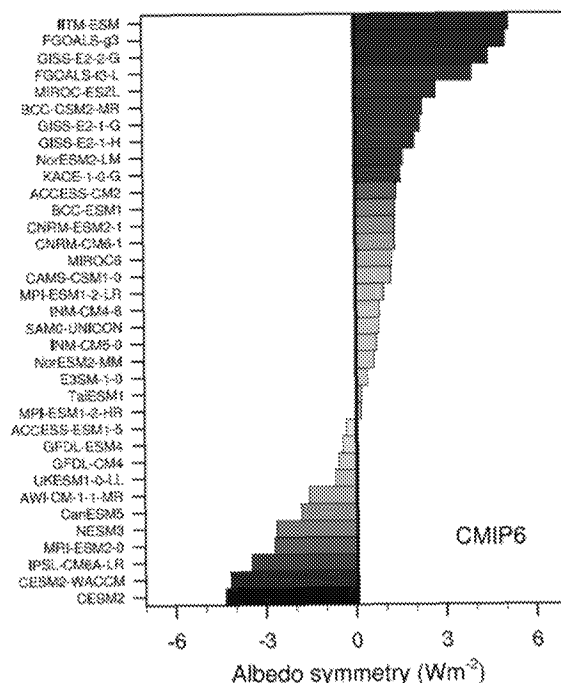


Figure 5.9. Differences in 20-year average reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

5.8 U.S. Corn Belt

One of the largest discrepancies between models and observations is in the U.S. Corn Belt, a region of particular importance to global food production. Figure 5.10 shows the warming trends for summertime (June, July, August) for the 12-state Corn Belt (IN, IA, IL, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) warm far too rapidly compared to observations (blue).

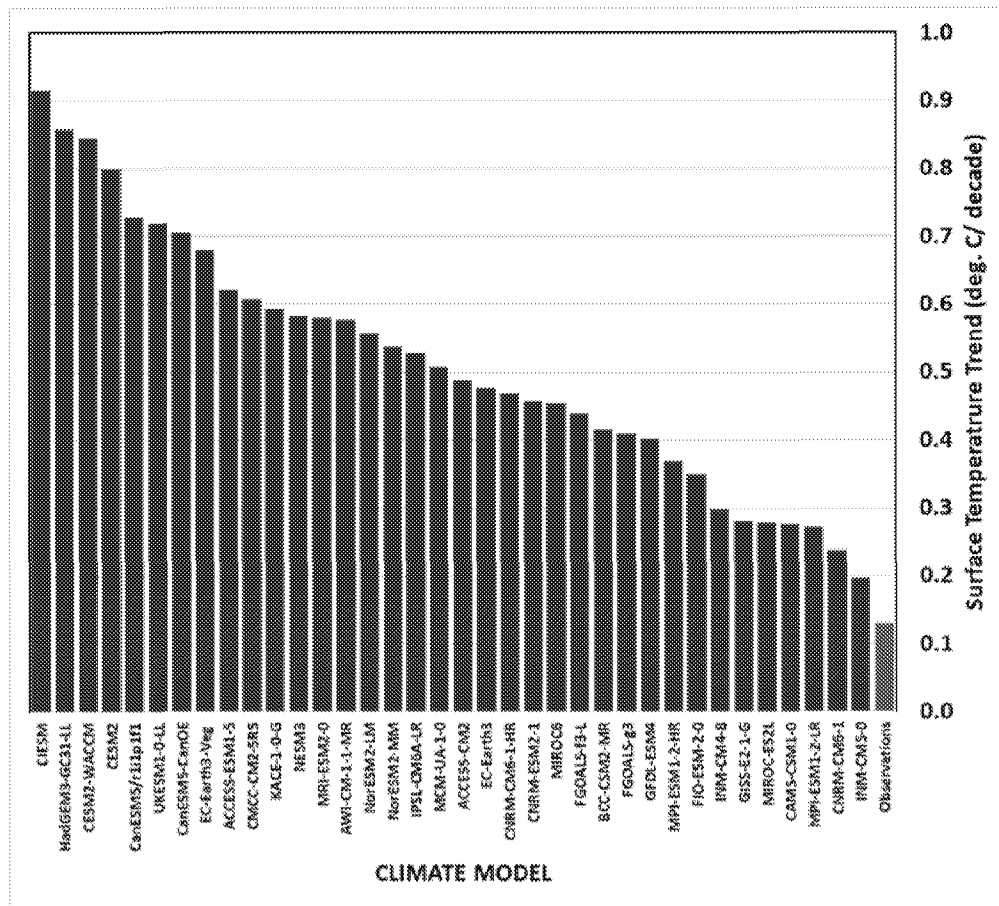


Figure 5.10: Modeled versus observed warming trends in the U.S. Corn Belt, 1973-2022.

As discussed in Chapter 9, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (*e.g.*, Seager *et al.*, 2018).

The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases might be sufficiently large that the models are simply not fit for purpose. As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from small scale processes, we believe that **the current generation of models is not fit for purpose**. (Palmer and Stevens 2019)

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the U.S. Corn Belt.

- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in W/m^2 is three times larger than the direct anthropogenic forcing of CO_2 .
- The IPCC has acknowledged some of these issues but not others.

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6 EXTREME WEATHER

Chapter Summary

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the U.S. since the 1950s, a point emphasized by AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability, but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but the trends do not persist over long periods and at the regional scale. Wildfires are not more common in the U.S. than they were in the 1980s. Burned area increased from the 1960s to the early 2000's, however it is low compared to the estimated natural baseline level. U.S. wildfire activity is strongly affected by forest management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., AR6 Seneviratne *et al.* 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. Further, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution to human-caused warming does not necessarily follow.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of Long-Term Persistence (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2016). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records that are short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

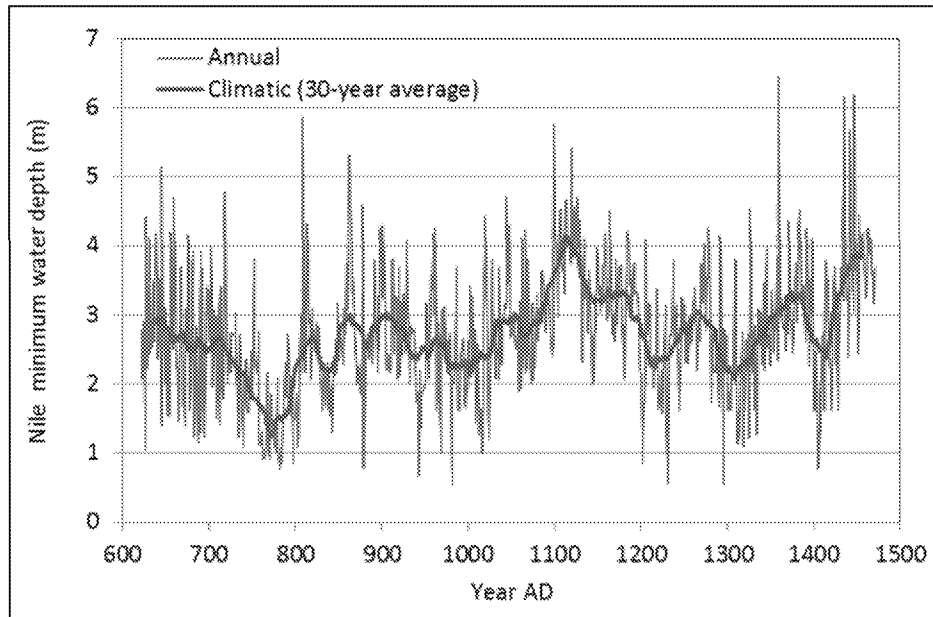


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from Koutsoyiannis (2013)

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. The Nile River is fed by precipitation over a 4 million square mile drainage basin, an area equal to about one third of CONUS. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eighth centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A recurring theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA4: The U.S. Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I.

NCA5: The U.S. Climate Science Special Report of the Fifth National Climate Assessment (2023) Volume I.

In the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

Additionally we present updated data series from standard government sources to provide up-to-date information through 2024 wherever possible.

6.2 Hurricanes and tropical cyclones

AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021 p. 1585)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2023 SPM p. 9)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC 2021 p. 1585)

Since 1980, when satellite observations first fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.2.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability, a weak decrease in the number of hurricanes, and a slight but insignificant increase in the number of major hurricanes. These two trends combine to create an overall increase in the proportion of major hurricanes.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (Colorado State University, 2025). Data in the Atlantic basin extends further back than in the other ocean basins and is most relevant to U.S. policy makers.

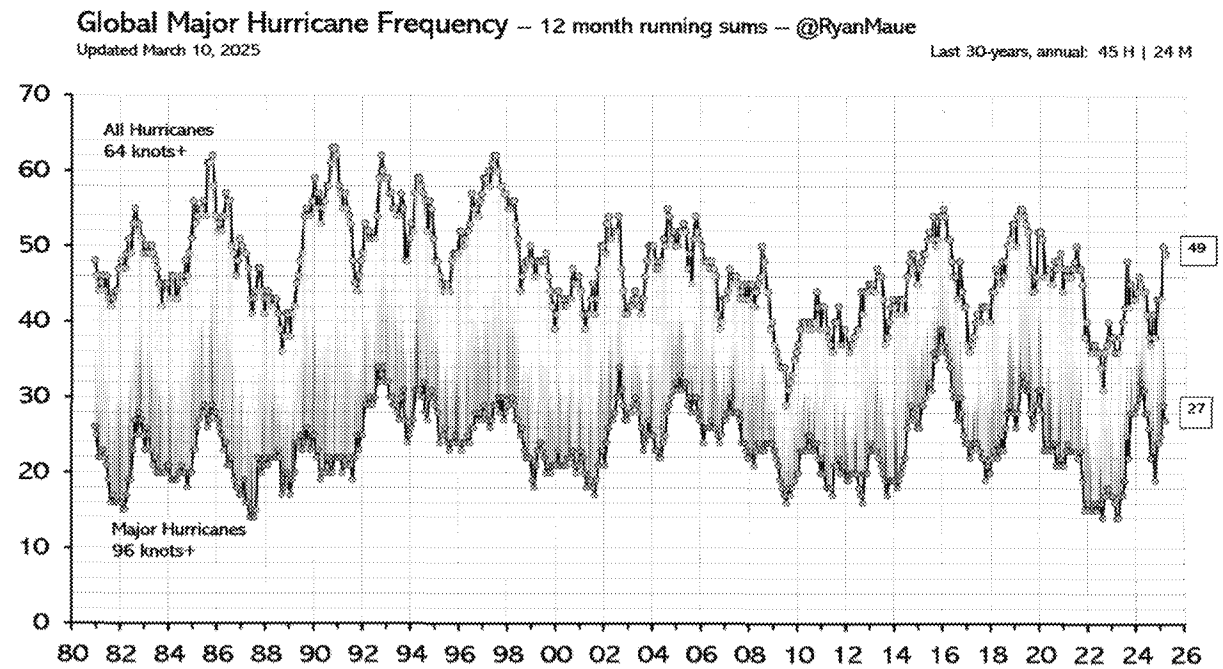


Figure 6.2.1: Global frequency of hurricanes and major hurricanes since 1980.

Figure 6.2.2 shows the frequency of Atlantic hurricanes and major hurricanes (Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (Vecchi and Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 saw exceptionally low activity, with high activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

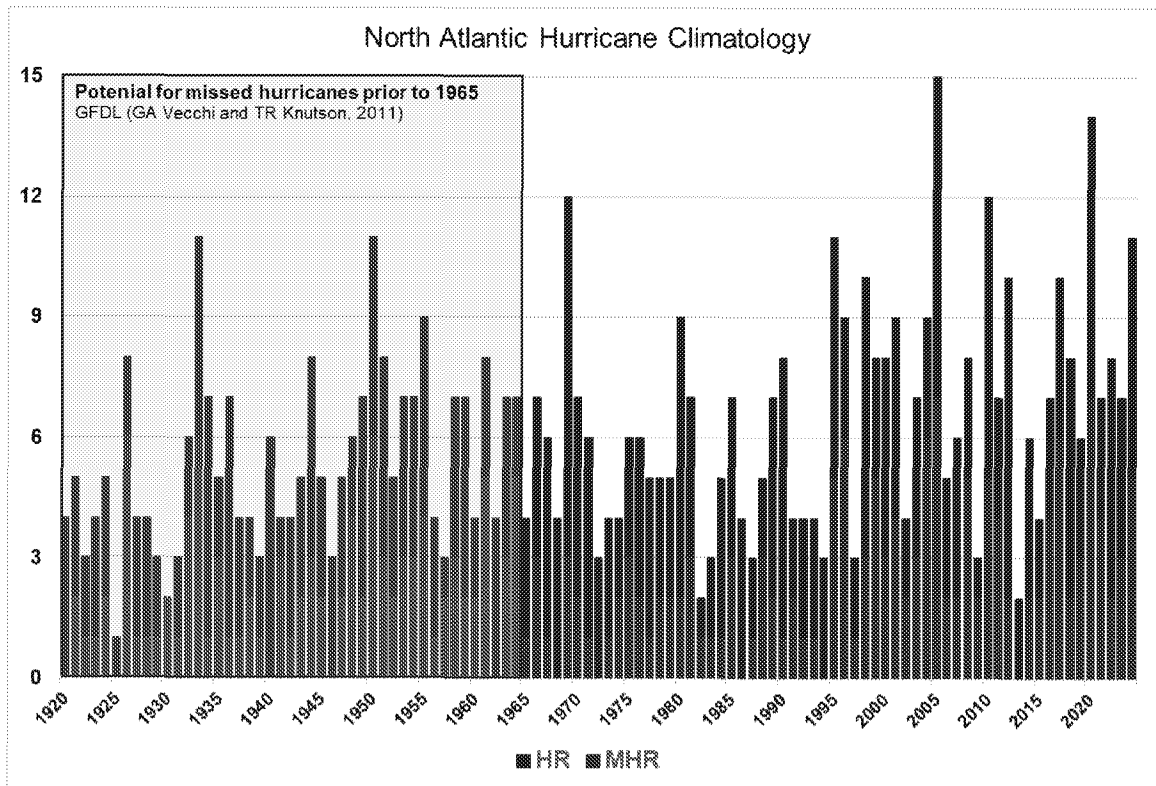


Figure 6.2.2: Atlantic frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source National Hurricane Center (2024)

Figure 6.2.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. It has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg *et al.* (2001) as associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach *et al.*, 2018).

Klotzbach *et al.* (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.2.3 updates their analysis through 2024. While the largest numbers of landfalling hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920. Figure 6.2.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, following 2005 there were no major hurricanes striking the U.S through 2016, the longest such period since 1920.

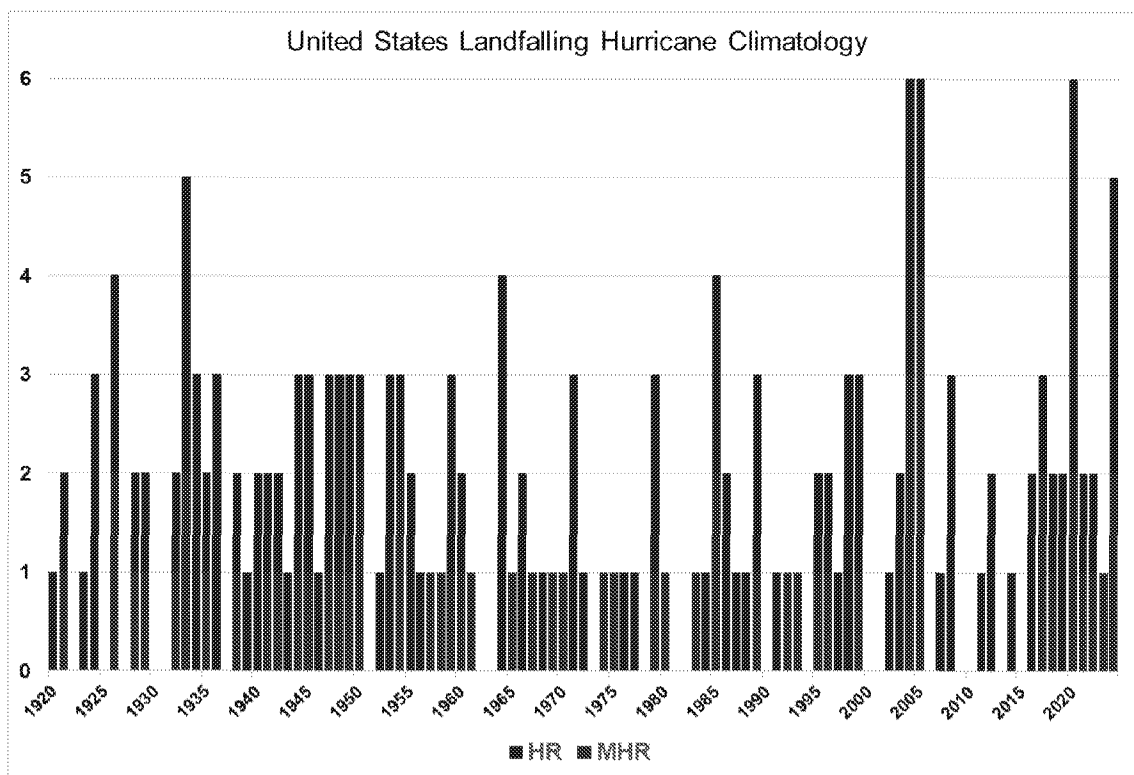


Figure 6.2.3: U.S. landfalling frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source NOAA HRD(a) (2024)

Figure 6.2.3 shows substantial interannual to multidecadal variability in U.S. landfall activity. Klotzbach *et al.* (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini *et al.* (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record is 1886, with 7 hurricane landfalls, when human influences on the climate were much smaller than they are today.

Table 6.2.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation. While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

Table 6.2.1 Strongest hurricanes to make landfall along the U.S. coast. Source (NOAA HRD(b), 2024)

6.3 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, NCA4 noted that heatwave activity in the U.S. reached a peak in the 1930s (Figure 6.3.1).

AR6: It is *virtually certain* that hot extremes (including heatwaves) have become more frequent and more intense across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe (SPM, A3.1)

AR6: In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA. (Chapter 11, p 1550)

NCA4: Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). (pp. 190-191)

NCA4: Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.** (pp. 190-191)

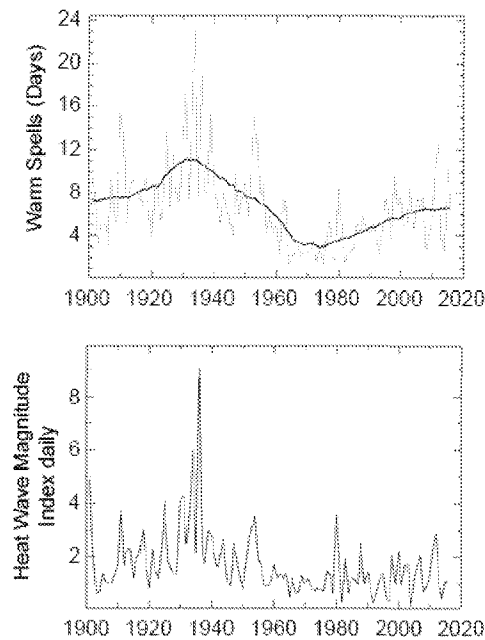


Figure 6.3.1: U.S. Heat waves since 1900. Source: NCA4 Figure 6.4

6.3.1 *Temperatures in the U.S. are becoming less extreme*

Daily maximum temperatures in the warm season (Tmax, May-Sep) and daily minimum temperatures in the cold season (Tmin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.3.2; Quinlan *et al.* 1987, Karl *et al.* 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves, and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, including unresolved spurious warming due to UHI effects that especially bias Tmin records, this data set is sufficiently accurate for assessing trends in Tmax heat extremes.

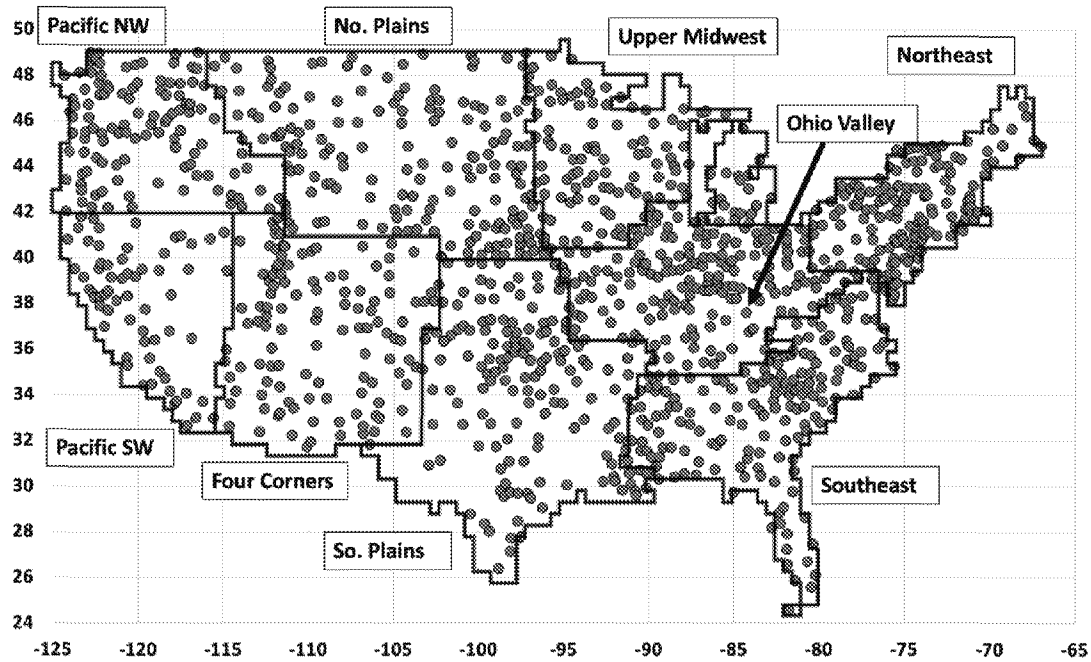


Figure 6.3.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for Tmax would be 1.21 ($=153/126$) per station per year and for Tmin 0.96 ($=122/126$) per station per year.

Figure 6.3.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60 percent of the Tmax records and 59 percent of the Tmin records occurred in the first half of the period (1899-1961).

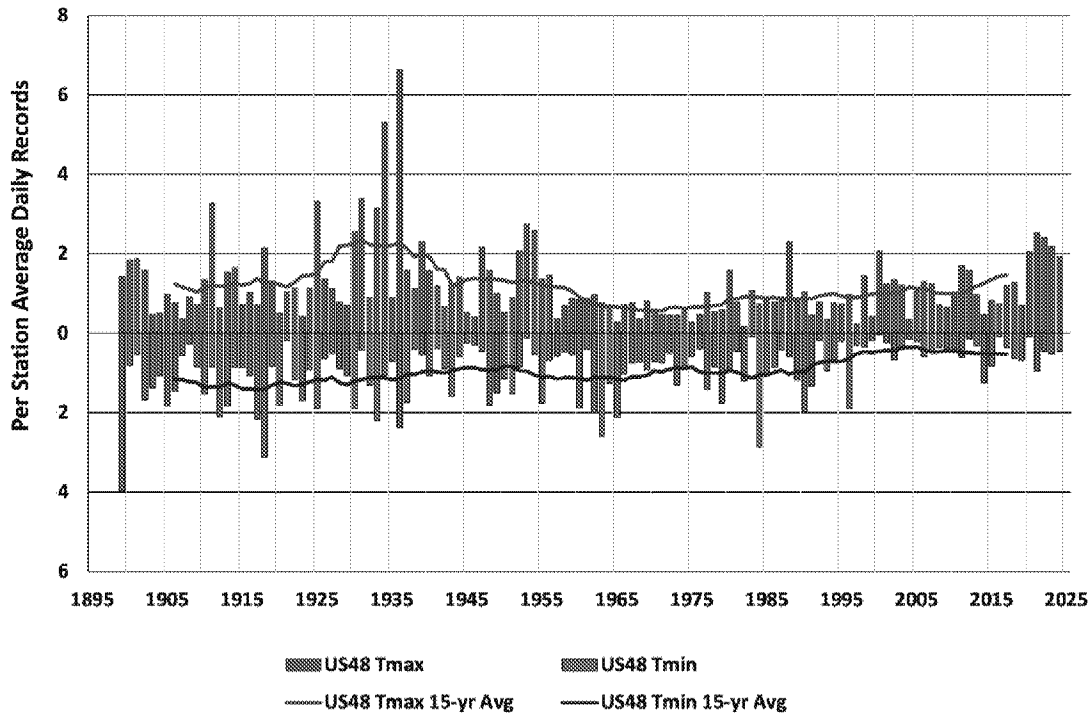


Figure 6.3.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92 percent of observations in the 126-year period since Dec 1898. US48: contiguous U.S. states. Tmax: maximum temperature. Tmin: minimum temperature.

On the cold side, the Valentine’s Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13 percent of the extreme cold events were measured. In contrast, 25 percent of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA4). Combining the two histories, the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.3.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.3.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

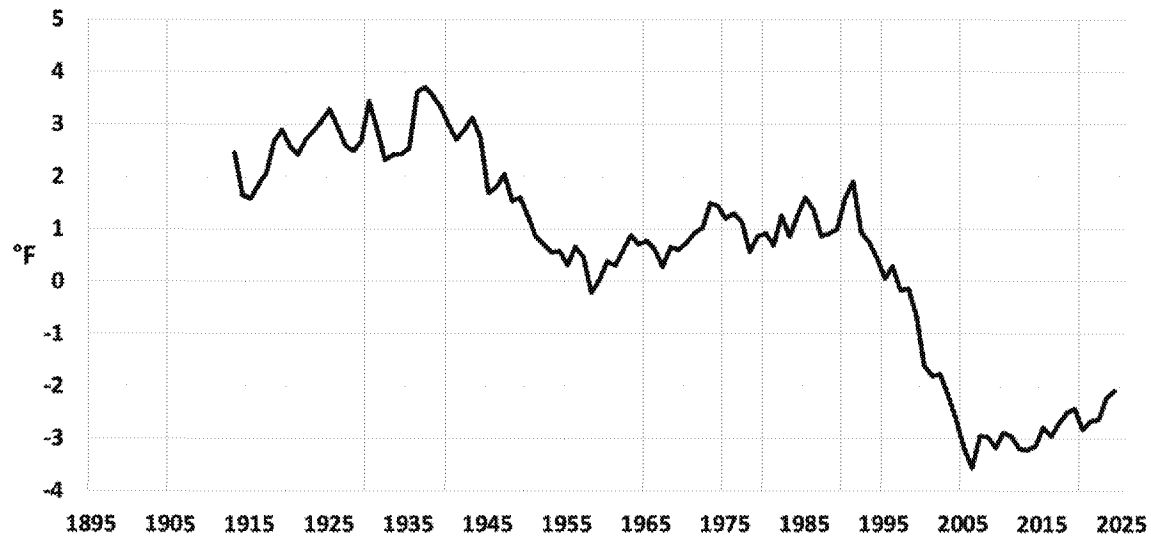


Figure 6.3.4. 15-year trailing average of the difference each year of each station's hottest warm-season Tmax and coldest cold-season Tmin relative to the long-term average. Source: Author analysis of USHCN data.

The average difference for each station between the hottest summer Tmax and coldest winter Tmin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter Tmin, but a decline in summer Tmax is also a factor. The rise in Tmin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Section 3.3 and Spencer *et al.* 2025).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the U.S. climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent U.S. National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

The western U.S. has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the U.S. since 2018, including a record-shattering event in the Pacific Northwest in 2021.

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F Tmax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F Tmax temperatures, a small change will not have much impact on the results.

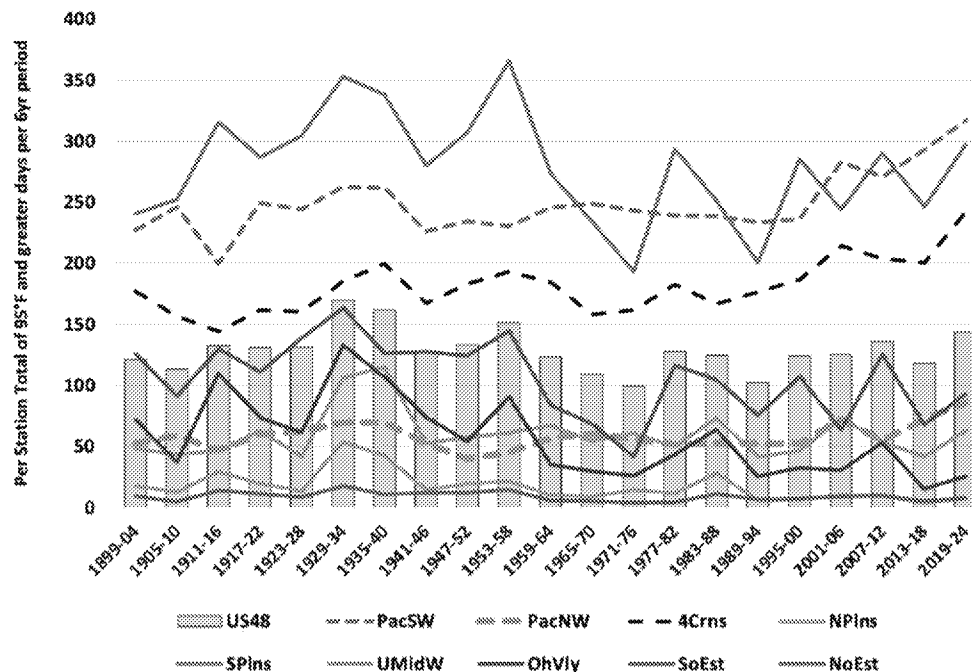


Figure 6.3.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, U.S. 48 (bars) and regions (lines). A 6-year period is used as this evenly divides the 126-year record. US48: contiguous U.S. states. See Figure 6.3.2 for region names. Source: Author analysis of USHCN data.

In the past 126 years, the average CONUS station experienced 129 days exceeding 95°C per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution. Figure 6.3.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA5 quote will be examined more closely in Section 8.6.1. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass *et al.* 2024).

The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA4, except that the reference period here is the entire record 1899-2024 while NCA4 truncated the reference period to 1961-1990, which was a cool interval. That truncation boosts positive results (days exceeding the 90th percentile) in years warmer than the reference period, especially starting in 1960 and moving to the present (see Figure 6.3.6 and discussion below).

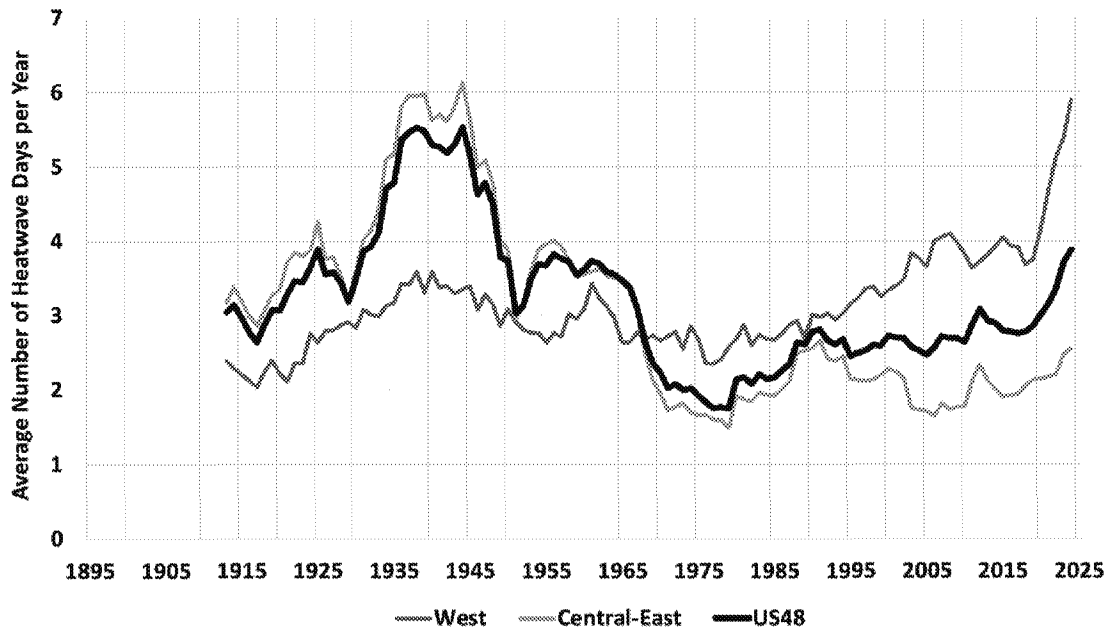


Figure 6.3.6 15-year trailing average of number of heatwave days per year per station in the CONUS (black line) and two regions: West (red), Central-east (green).

Figure 6.3.6 indicates that there are regional variations in heatwave activity. The excessive heat of the first half of the 20th century occurred primarily in the eastern two-thirds of the nation, while the West has seen a recent increase of heatwave days (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA4.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

The analysis of heatwaves is an example of why it is important to consider complete datasets and appropriate metrics. The NCA5 directs readers to the website [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)] (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.3.7.

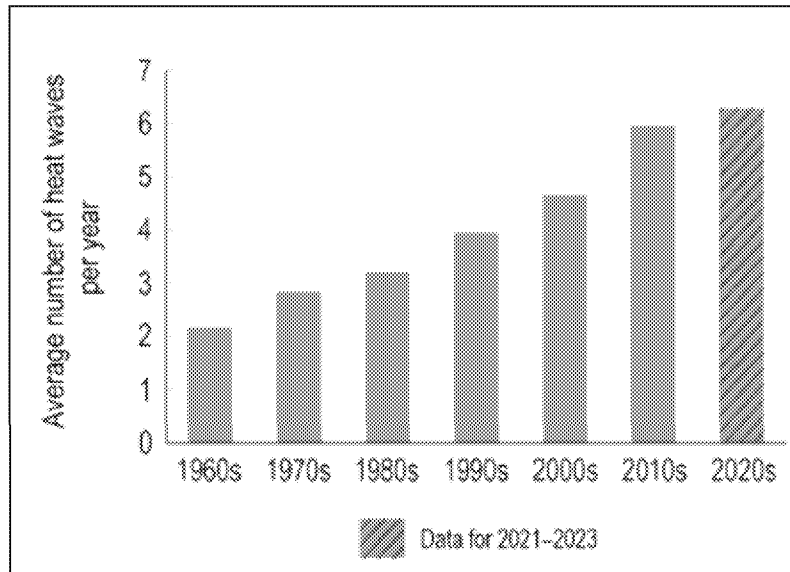


Figure 6.3.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas, a misleading metric for reasons explained in the text. From [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)] (accessed May 22, 2025).

The figure shows a monotonic increase in each decade from two occurrences per year in the 1960s to six in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the *minimum* apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

Given the unusual heatwave definition and urban focus, these increasing values since 1960 presented in USGCRP (2023) are not informative about long term trends or the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.3.1 and 6.3.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of T_{min} relative to co-located T_{max} and relative to T_{min} at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons that summer T_{max} (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy *et al.* 2009). For CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves against the background of urbanization and natural climate variability.

6.4 Extreme precipitation

AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence). (SPM A3.2)

AR6: In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has *very likely* increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018. (Chapter 11, p. 1560)

The U.S. National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes (Figure 6.3.6).

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast using a trend model with a non-parametric variance estimator robust to the complex autocorrelation properties of precipitation data. When the time series were extended back in time (as far as 1872 in some cases) or started later (1978), there were no significant trends for either region.

These findings have been updated for this report (McKittrick and Christy 2025) with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.4.1. The stations were selected based on availability of long-term high-quality records. The regions are each associated with important features of extreme precipitation behavior: the Pacific coast is associated with landfalling atmospheric rivers for which AR6 cites evidence of increasing activity since 1948 with further increases expected as the world warms (AR6 8.3.2.8.2); the NCA report indicates that the Northeast has experienced the greatest increase in extreme events, and the Southeast is also a place noted in the NCAs as having increased extreme events.

The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.

Pacific Coast heavy rainfall events

- The average precipitation trend is statistically significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov *et al.* 2017, Pan *et al.* 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred during December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter *et al.* 2011).



Figure 6.4.1: Locations of precipitation monitoring stations used in this report. Orange: Pacific coast. Blue: Northeast. Green: Southeast. Data from McKittrick and Christy (2025).

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year might have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly spread over the years. In Fig. 6.4.2 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

Southeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in Mobile AL and Quitman GA but insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA but insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.4.3 is analogous to Figure 6.4.2 for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

BOX: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps because of human influences. [Note “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. And comparing the records of the two charts shows the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme listed in Table 6.2
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter *et al.* (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (Section 8.6). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50 percent determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

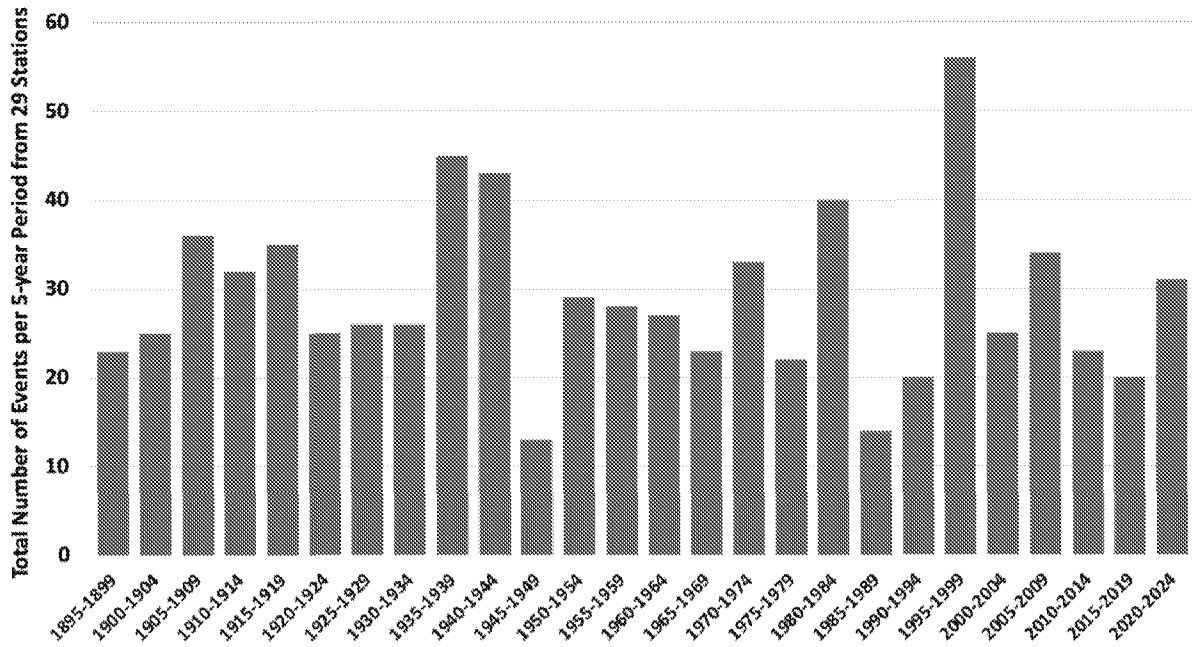


Figure 6.4.2. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

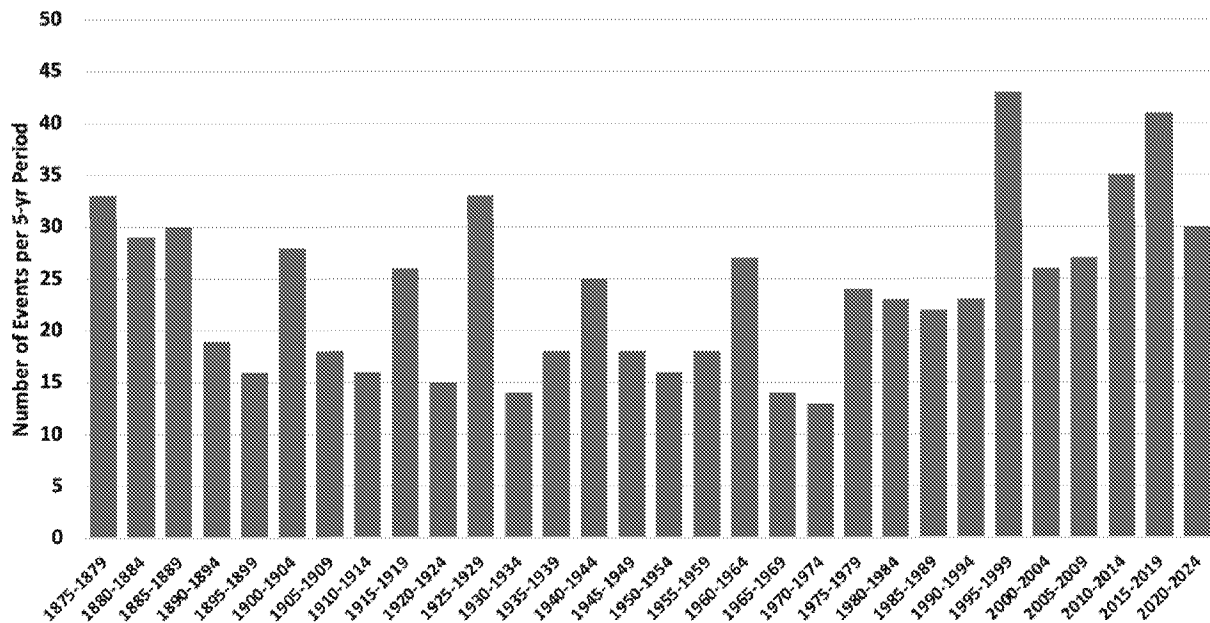


Figure 6.4.3. As in Fig. 6.4.2 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

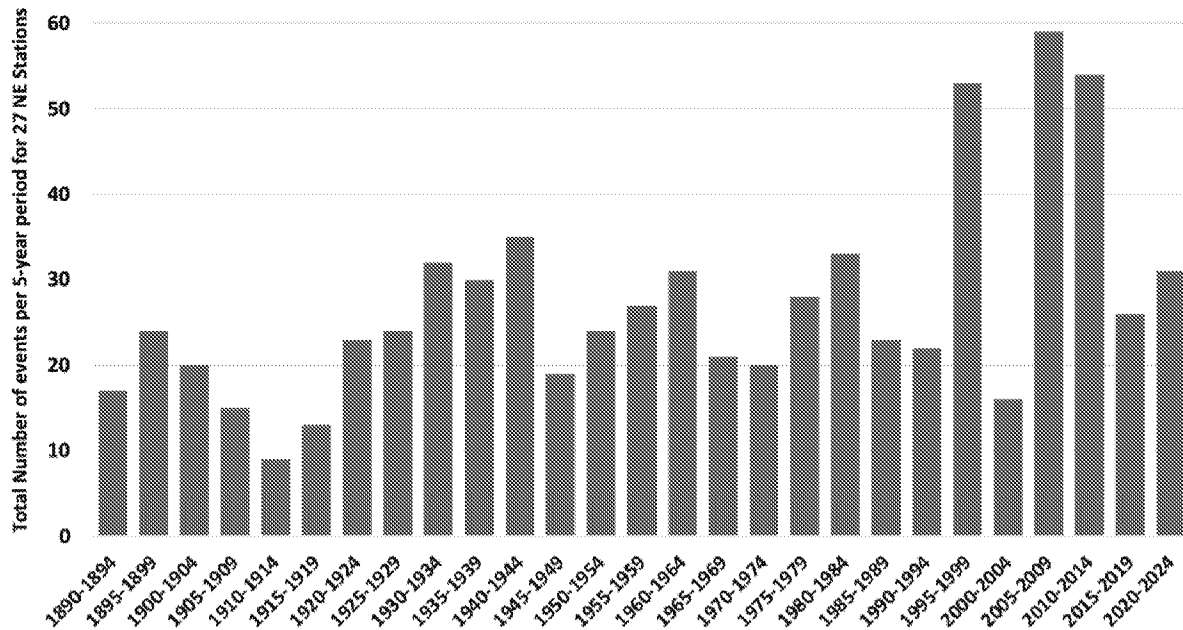


Figure 6.4.4. As in Fig. 6.4.2 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 27 Northeast stations from NY to ME, including Montreal.

Northeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in 12 of 27 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY, Buffalo NY and Eastport ME but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME, Gardiner ME and Eastport ME but insignificant elsewhere.
- When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

Fig. 6.4.4 is analogous to Figure 6.4.2 for the last 135 years in 27 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 77 percent of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it merits a closer examination.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth *et al.* (2019) examined a similar region as in Fig. 6.4.4 that includes PA and NJ and reported significant differences in various precipitation extremes between two 18-year periods, 1979-96 and 1997-2014. That included a 317 percent increase in 24-hr events exceeding 6 inches, while we find a 58 percent increase over the same years. However, Figure 6.4.4 shows that frequency drops sharply after 2014, returning to the long-term average in the subsequent 5-year intervals, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

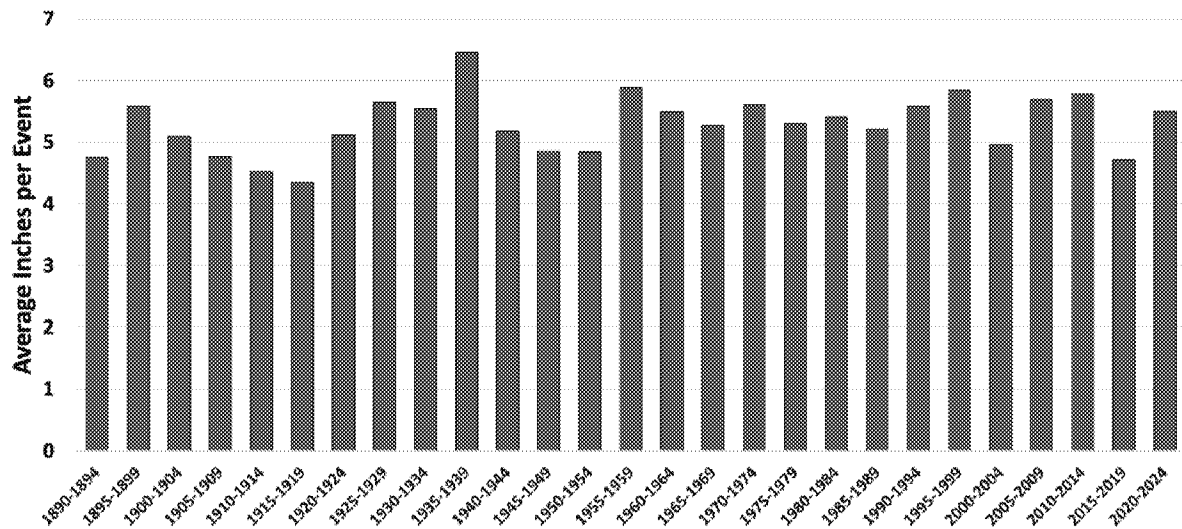


Figure 6.4.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

The high percentage increase in the Howarth *et al.* sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.4.5 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only +0.04 inches/decade. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.4.4 and 6.4.5 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

Jong *et al.* (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded “The autumn extreme precipitation trend over the Northeast U.S. is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: “Was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs?” Jong *et al.* examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.4.5 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events might be redistributed due to the impact of urban infrastructure on the local weather (e.g., Pielke Sr. *et al.* 2011, Zhang *et al.* 2018, Yang *et al.* 2024). Yang *et al.* state “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.4.5.

In summary, some U.S. regions show short-duration increases in extreme precipitation events, consistent with natural variability. But analysis of long term, nationwide historical records that considers the autocorrelation properties of precipitation data does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.5 Tornadoes

AR6 assesses tornado trends in the U.S. as follows:

[O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

The monitoring of weak tornadoes has changed over time. The growth of rural populations and the increasing ability to take video with hand-held devices has led to more frequent reports of weak tornadoes that produce minimal damage. In contrast, strong to violent tornadoes have been observed more consistently over time. Note that tornado strength is measured by the damage it produces, not by the visual appearance of the funnel. Limited real-time observational capabilities in earlier decades did not prevent identification because strong to violent tornadoes leave much more damage which will be assessed later even if the tornado itself was not observed. Since statistics began in 1950, there has been a substantial decrease (by about 50%) in the number of strong to violent tornadoes as shown in Fig. 6.5.1a.

To summarize, there is a noticeable downward trend in the number of severe tornadoes in the U.S. since 1950. After 1990 the number of weak tornadoes in the U.S. has remained roughly constant; data before that are incomplete due to limited monitoring.

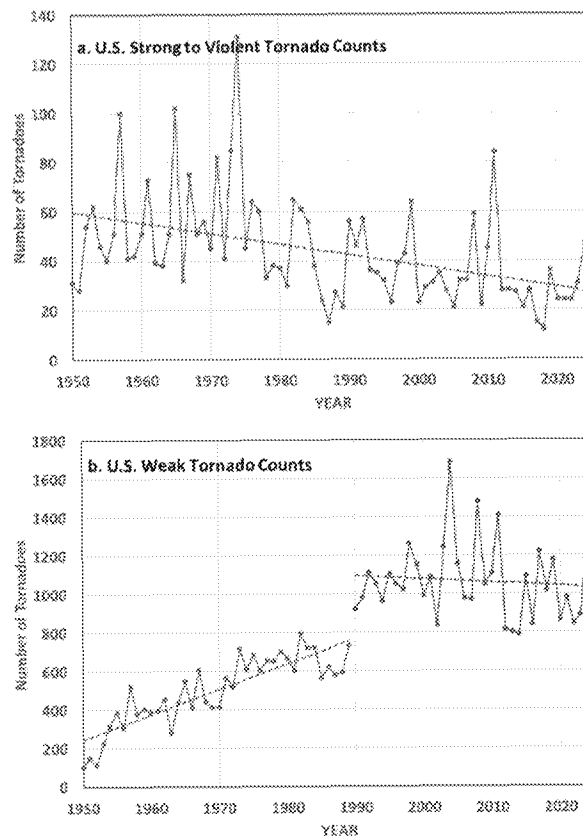


Figure 6.5.1. Annual U.S. tornado counts for (a) strong to violent tornadoes (EF3 to EF5), and (b) weak tornadoes (EF0 to EF2). Based upon NOAA Storms

Prediction Center data, available at https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv

6.6 Flooding

Changes in floods were assessed as follows:

AR6: The SREX **assessed low confidence for observed changes in the magnitude or frequency of floods** at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales. (Chapter 11.5)

AR6: [T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*. (Chapter 11.5)

NCA4: Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude **but does not provide robust evidence** that these trends are attributable to human influences (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in Section 6.4 of absence of coherent changes in extreme precipitation.

6.7 Droughts

Assessments of drought trends were as follows.

AR6: Few AR6 regions show observed increases in meteorological drought (Section 11.9, p. 1575),

AR6: Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions. (Chapter 11 Summary)

NCA4: As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined**. (p. 233)

NCA4: Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence). (p.231)

SREX: From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia. (p. 170)

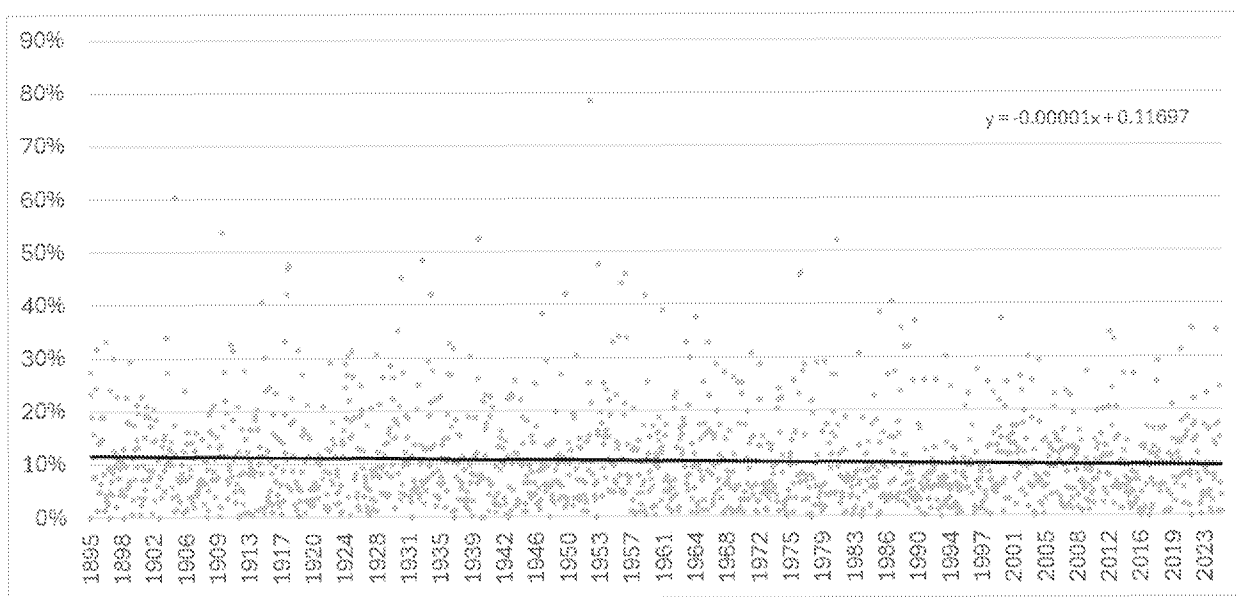


Figure 6.7.1: Monthly percent of US classified as “Very Dry” 1895—2025. Data source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)] least squares trendline added.

As shown in Figure 6.7.1, U.S. long-term data shows an insignificantly declining trend in extreme dryness (-0.001 percent per year)

Kogan *et al.* (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

In summary there is no evidence of increasing drought frequency or intensity in the U.S. or globally over recent decades.

6.8 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.8.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.

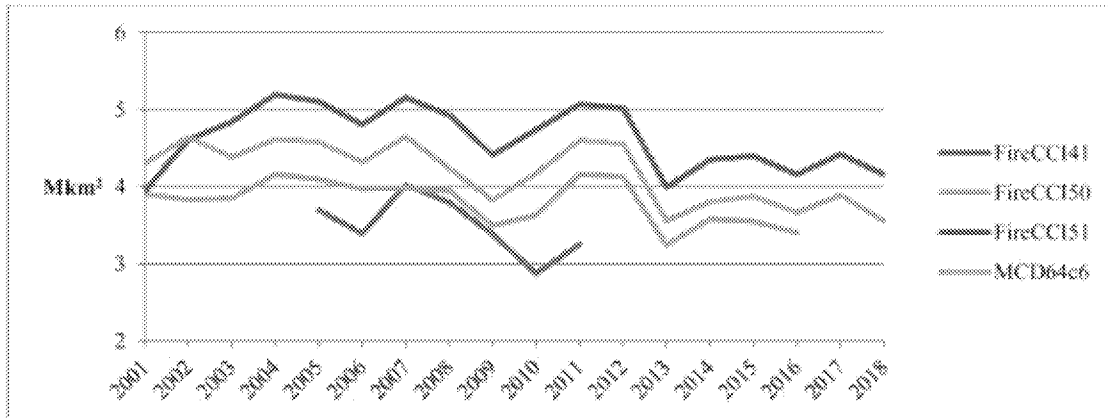


Figure 6.8.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola *et al.* (2021) Figure 12. The different coloured lines represent data products derived from different satellites and algorithms

Global data show that wildfire coverage is constant or declining on every continent (Samborska and Ritchie, 2024).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. Paleoclimatic evidence indicates that past activity was much higher than today. Marlon *et al.* (2012) used sedimentary charcoal layers to reconstruct fire history of western U.S. for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.8.2 below (from Figure 2 in their paper). There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks *et al.* (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

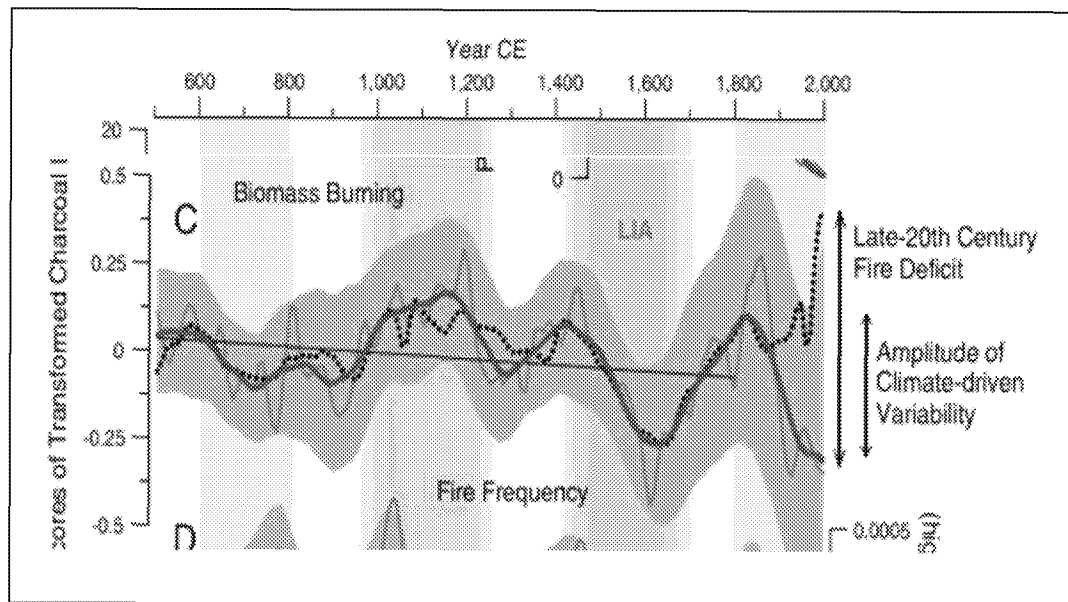


Figure 6.8.2 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on climatic conditions. Source: Marlon *et al.* (2012) Figure 2.

U.S. data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.8.3. The NIFC has removed the pre-1960 data from its current website on the grounds that measurement methods changed after 1960 making the comparison unreliable. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life, including humans. Science has confirmed the overall benefit and necessity of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile U.S. forest fire remains the 1910 Big Blowup fire in the U.S. west, which destroyed over three million acres and eliminated entire towns like Taft, MT (Apple, 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal of defeating all forest fires (Forest History Society, 2022). This led to the “10 am rule” in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation, 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (U.S. Forest Service, 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and controlled wildfires are more appropriate (Sommer, 2016). Recent research is validating this approach and recognizing that more frequent smaller fires likely result in healthier forests, water ecosystems and biodiversity (Stephens *et al.*, 2021).

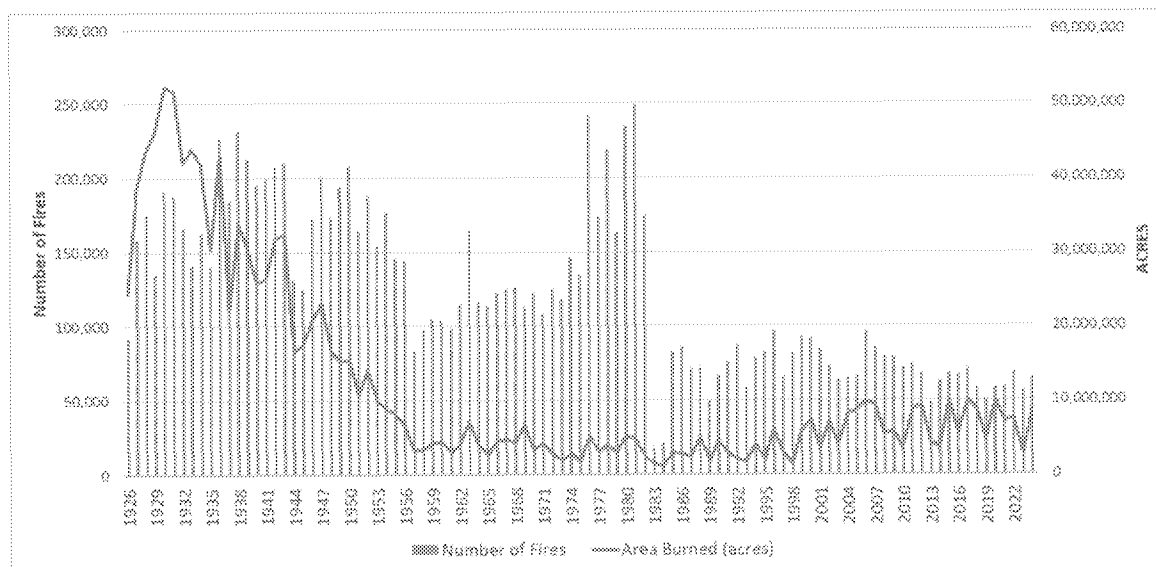


Figure 6.8.3: U.S. wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Center data [[HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"](https://www.nifc.gov/fire-information/statistics/wildfires)]. Pre-2017 webarchive.org (n.d.).

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7 CHANGES IN SEA LEVEL

Chapter Summary

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also with ocean circulation patterns. The largest sea level increases along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothetical ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the interval has elapsed by 2025, with sea level rising at a lower rate than predicted. U.S. tide gauge measurements reveal no obvious acceleration beyond the historical average rate of sea level rise.

7.1 Global sea level rise

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (Fox-Kemper *et al.*, 2021). The rate of global sea level rise is estimated to be 0.12 inches/year, about the height of two stacked pennies (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters in 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860, well before most anthropogenic greenhouse gas emissions.

7.2 U.S. sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 7.1 shows that in Canada and Alaska (and also northern Washington), sea level is decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show low rates of sea level rise, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

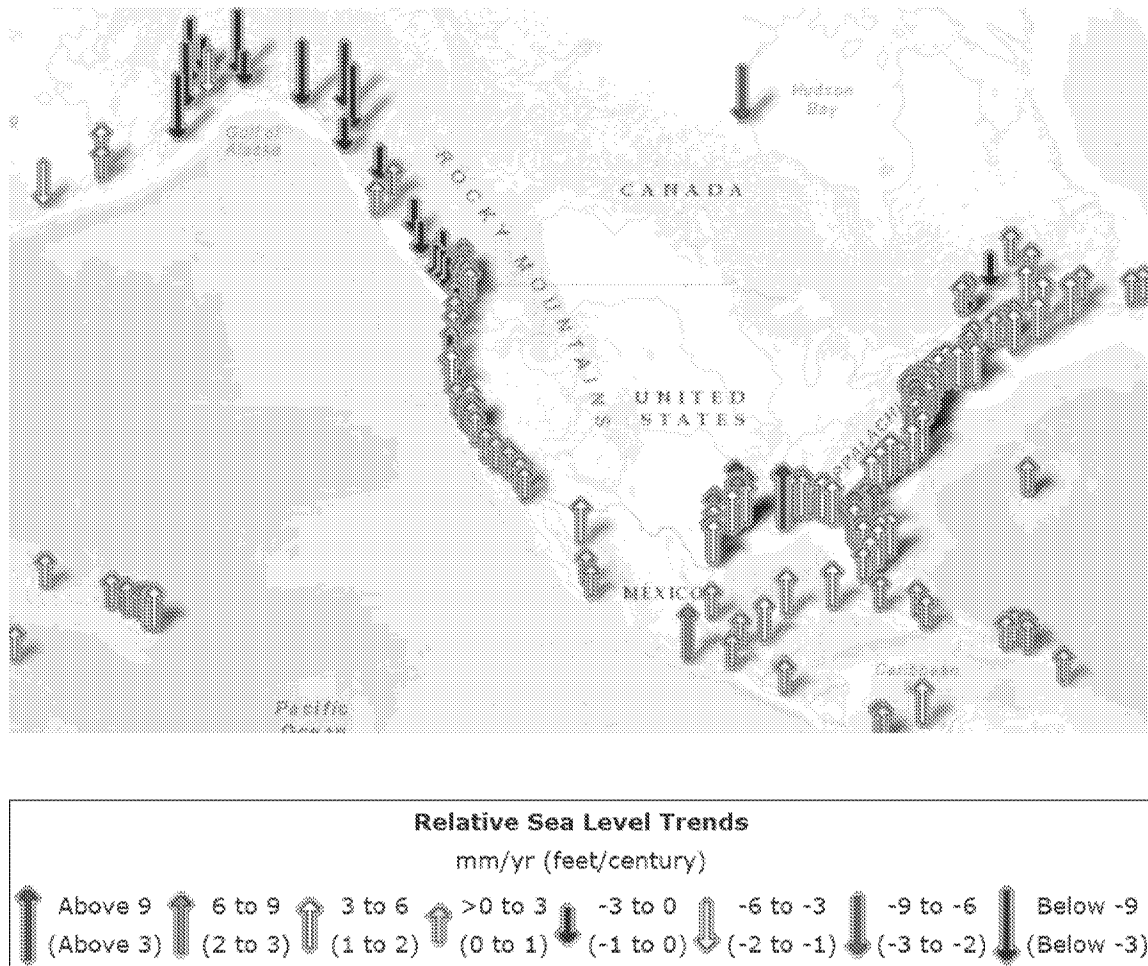


Figure 7.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. The latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (Wöppelmann and Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (*e.g.* for urban development) and subsurface extraction of groundwater or hydrocarbons.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; Letetrel *et al.*, 2015; Karegar *et al.*, 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

Table 7.1 Absolute sea level rise (inches/year) consisting of Relative Sea Level Rise (RSLR) plus Vertical Land Motion (VLM)

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.2). As shown in Table 7.1, San Francisco’s vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (Shirzaei and Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, are caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

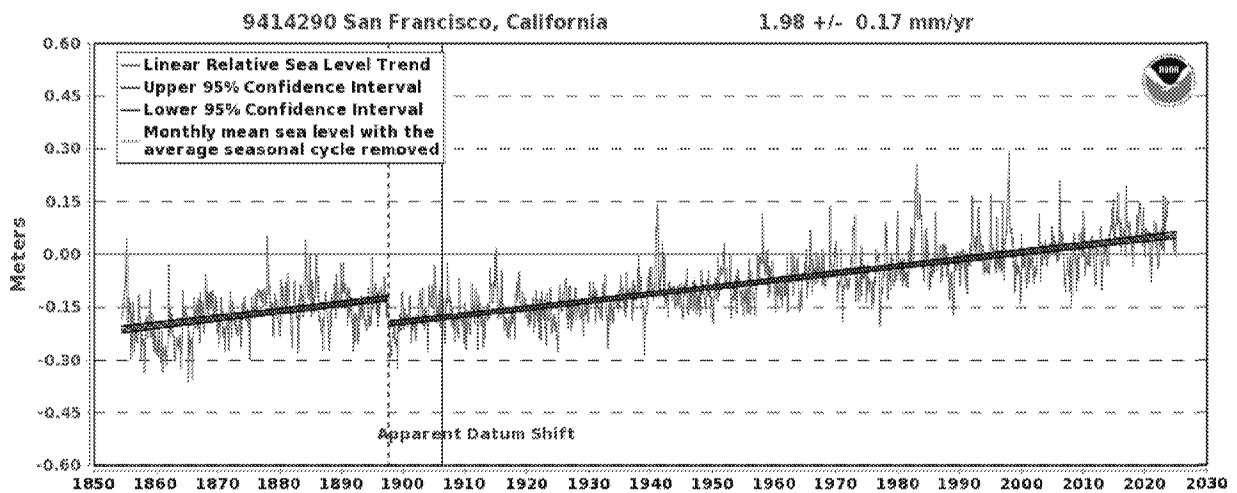


Figure 7.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (Kasmarek and Ramage 2017), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

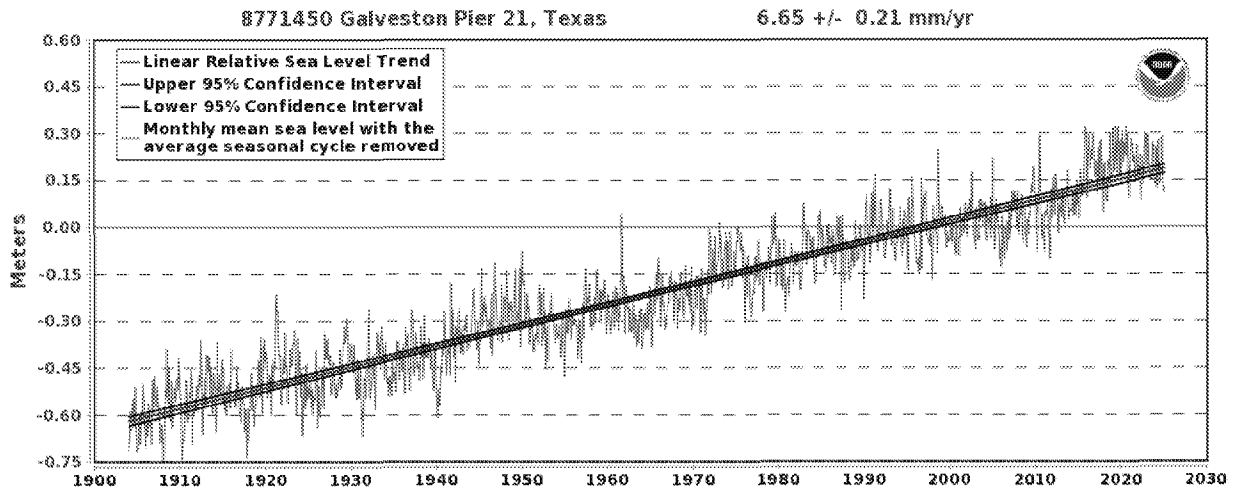


Figure 7.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 7.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 7.1 gives the absolute sea level rise as +0.08 inches/year.

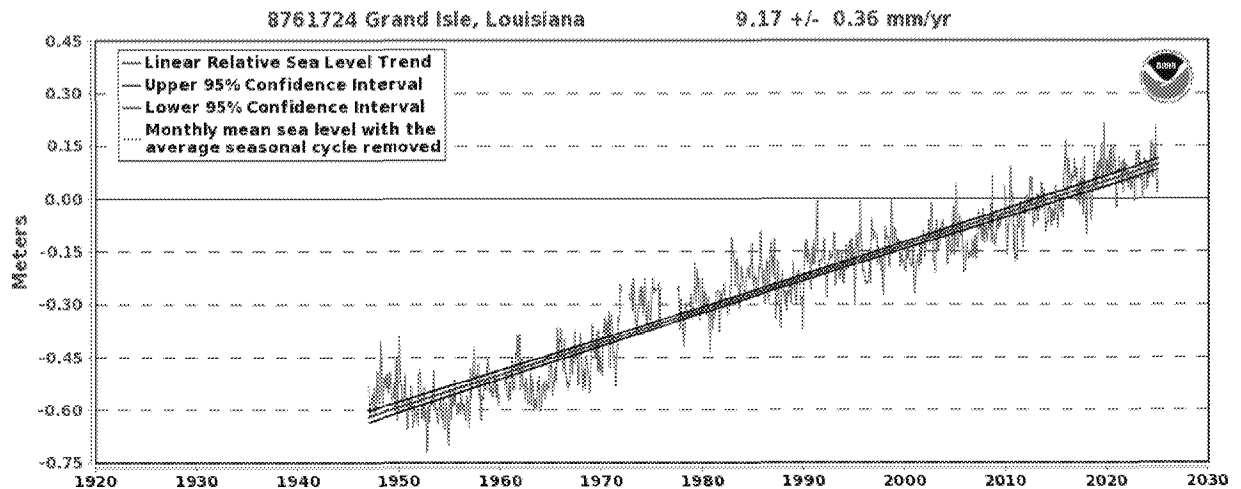


Figure 7.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi River being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi’s suspended sediment load by ~50 percent (Maloney 2018). A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (Neinhuis *et al.* 2017), associated with groundwater and resource withdrawal. As the city’s elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans’ problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (The Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55 percent of the measured relative sea level rise.

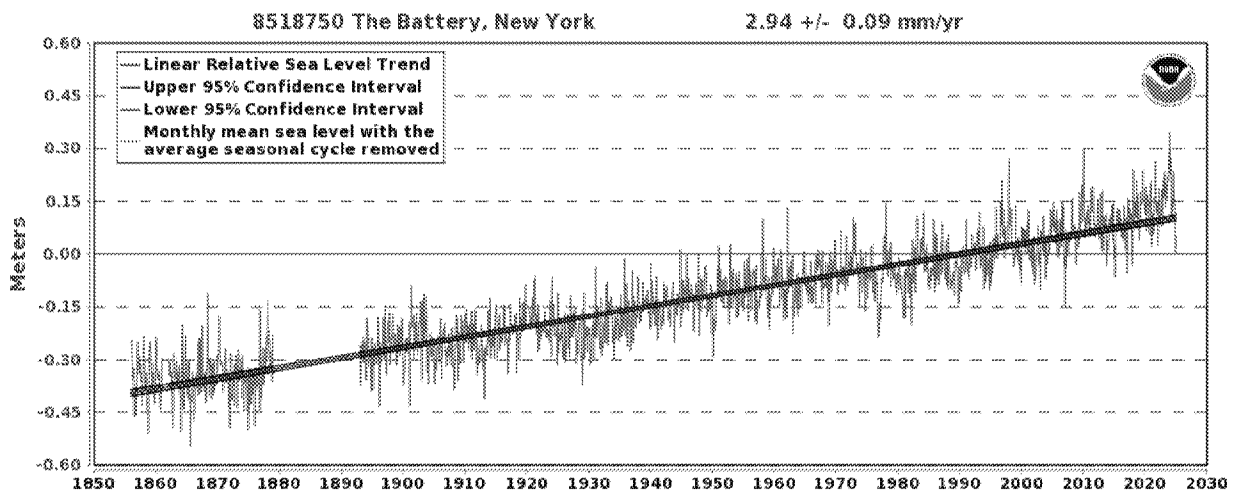


Figure 7.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

7.3 Projected sea level rise

The concern over sea level rise is not about the roughly eight inches of global rise since 1900. Rather, it is about projections of *accelerated* rise based upon simulations of a warming climate through the 21st century.

AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (Fox-Kemper *et al.*, 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (Fox-Kemper *et al.*, 2021). There is deep uncertainty surrounding projections of sea level rise to 2100 owing to uncertainties in ice sheet instabilities, particularly for the higher emissions scenarios.

In February 2022, NOAA issued its projections of sea level rise for various sites along the U.S. coast (Sweet *et al.*, 2022). They claim that by 2050, the sea will have risen one foot at The Battery in Manhattan (relative to 2020). A one-foot rise in thirty years would be more than twice the current rate and about three times the average rate over the past century. In that historical context, NOAA’s projection is remarkable—as shown in Figure 7.6, it would require a dramatic acceleration beyond anything observed since the early 20th century. But even more noteworthy is that Sweet *et al.* (2022) say this rise is “locked in”—it will happen no matter what future emissions are. We should know in a decade or so whether that prediction has legs.

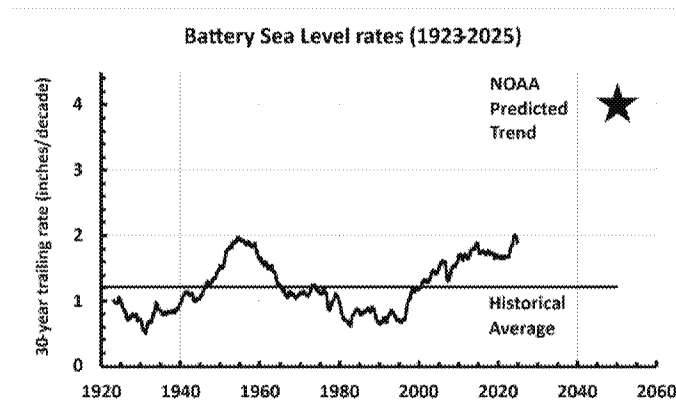


Figure 7.6 Rate of sea level rise at the Battery in Manhattan. Shown is the historical thirty-year trailing trend, together with the allegedly “locked in” NOAA predicted trend for 2050. Historical data: NOAA Tides and Current.

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8 UNCERTAINTIES IN CLIMATE CHANGE ATTRIBUTION

Chapter summary

“Attribution” refers to identifying the cause of some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and in aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (*e.g.* event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the AR6 WGI Glossary (IPCC, 2025):

Detection: Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.

Attribution: Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.

Both detection and attribution rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities (such as GHG emissions) versus natural factors (like volcanic eruptions) contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl *et al.*, 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer *et al.*, 2014) makes the following statement:

Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key IPCC attribution methods.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model is weighted to try to minimize the influence of random noise and the estimation method is chosen to account for climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (*e.g.* heat waves or droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: **Most of the observed increase** in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations. (IPCC 2007)

AR5: It is *extremely likely* that **more than half of the observed increase** in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period. (IPCC 2013)

AR6: The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that **well-mixed GHGs were the main driver** of tropospheric warming since 1979. (IPCC 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began increasing rapidly. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99 percent of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 5, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulations.

Solar variability

AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m², Myrhe *et al.*, 2014). AR6 acknowledges substantially higher values and a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by 0.7–2.7 W/m², a range that includes both low and high variability TSI data

sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact of solar forcing on the climate was still assessed to be small compared to anthropogenic forcing. However, the impact of solar variations on the climate is uncertain and subject to substantial debate (Lockwood, 2012; Connolly *et al.*, 2021) - something that is not evident in the IPCC assessment reports.

The variations of TSI over time remains a challenging problem. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets that disagree as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models that infer past solar variations from sunspots and cosmogenic isotope measurements (Velasco Herrera *et al.*, 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos *et al.*, 2023; Solanki *et al.*, 2004; Usoskin *et al.*, 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70 percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta *et al.* (2023) suggests that ~80 percent of solar influence on climate might stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models have too little amplitude compared to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov *et al.* 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (*e.g.* CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the AR5 and AR6 reports:

AR5: Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.

AR6: Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (*high confidence*).

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to $+0.2^{\circ}\text{C}$ (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C . Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out owing to differences in phasing, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 (Figure 8.1) shows irregular variations of significant amplitude against the background of an overall warming trend and, after 1976, a pronounced difference in trends between the Northern Hemisphere and the Southern Hemisphere. The period between 1905-1945 shows a strong trend of warming. The following 30 years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

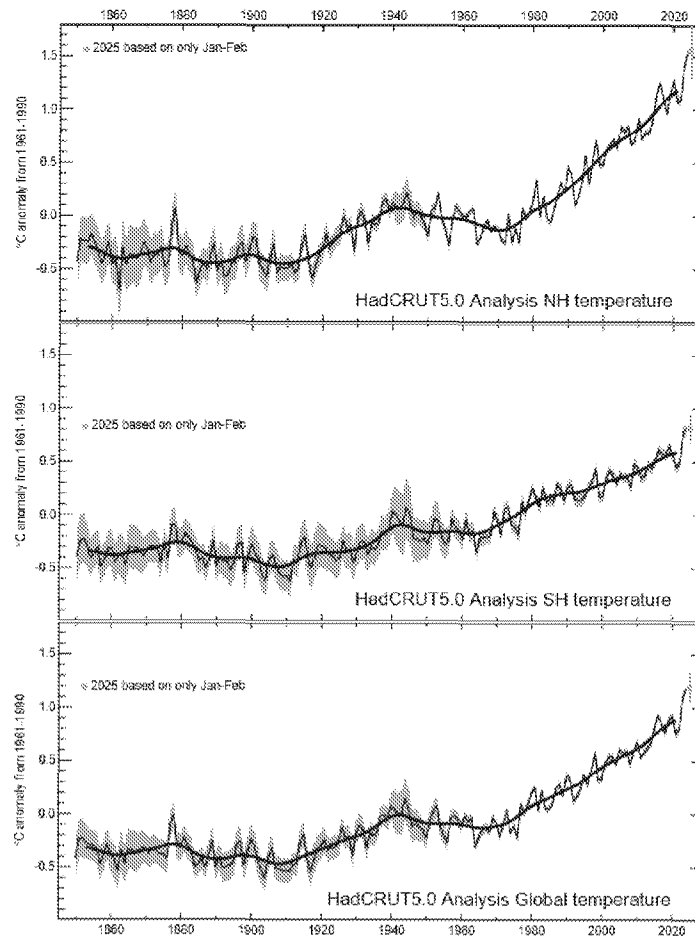


Figure 8.1 Global average surface temperature anomalies 1850—2025. Top: Northern hemisphere. Middle: Southern hemisphere. Bottom: Global average. Source: UK Hadley Centre [HYPERLINK "<https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf>"]

The causes of the early 20th century warming are discussed by Hegerl *et al.* (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941, implying that CO₂ had little impact. Volcanic activity during this period was very low, and solar forcing is uncertain. Yet Hegerl *et al.* (2017) somehow inferred that 40-54 percent of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman *et al.* (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid-century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that these variations were most likely caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity, as well as growing greenhouse gases concentrations. Tokinaga *et al.* (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic

warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale circulations over the Northern Hemisphere; these same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson *et al.* (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns, including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean *et al.*, 2009; Tung and Zhou, 2013; Chylek *et al.*, 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or “fingerprints”) associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares (TLS). The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001, there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2021, 2022, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2021) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen *et al.* (2023) confirmed this analysis, although they argued that the method could yield valid results under very stringent assumptions. McKittrick (2022) and (2023) raised a further concern that climate scientists—virtually alone among

scientific disciplines—have used TLS to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unstable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS estimates have a large positive bias. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the attribution.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2023) using a different estimation method and multiple independent data sets.

While these analyses do not falsify results of the IPCC optimal fingerprinting method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades *et al.*, 2016, Balcombe *et al.*, 2019, Dagsvik *et al.*, 2020, Razzak, 2022, Dagsvik and Moen, 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable, we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson *et al.* (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data, the coherence in the series is primarily due to the influence of temperature on CO₂ levels, not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time

series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also increased abruptly in recent years. The question is whether the change is an internal feedback to warming caused by greenhouse gases, or whether something else increased the fraction of absorbed radiation which then caused the recent warming.

The planetary albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important in this regard. The Earth's albedo is approximately 30 percent, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in planetary albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.2 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5 percent reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in absorbed solar radiation averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Goessling *et al.* (2025) assessed that the planetary albedo was relatively low around the 1940's and 50's before rising industrial aerosol precursor emissions increased the albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum might have been the lowest since at least 1940.

Changes in surface characteristics cannot explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5 percent since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England *et al.*, 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (Summary for Policymakers, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer, see [[HYPERLINK "http://climate.rutgers.edu/snowcover/"](http://climate.rutgers.edu/snowcover/)] and Section 5.6
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo decrease associated with increasing forested area.

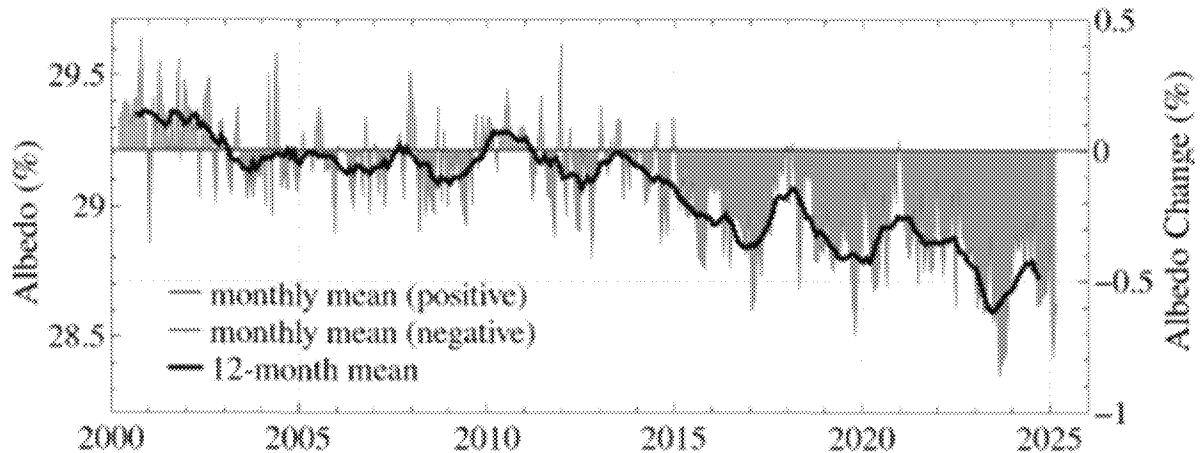


Figure 8.2. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor of three on average, primarily due to cloud masking (Loeb *et al.* 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally. This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (*e.g.* dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall might produce less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog *et al.*, 2024; Yuan *et al.*, 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

Changes in clouds are the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb *et al.*, 2024; Goessling *et al.* 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb *et al.* found that decreases in low- and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Goessling *et al.* (2024) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The issue then becomes the cause of the change in cloud cover. Two explanations have been posited for the declining cloud cover over the past decade:

- Natural climate variability

- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

It is not easy to justify a new positive low cloud feedback that began emerging in 2015. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was one of the strongest El Niño events on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams *et al.*, 2017; Arthun *et al.* 2021).
- The Pacific Decadal Oscillation positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO) have a significant global signal and strong regional signals, especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Goessling *et al.* (2024) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz *et al.*, 2025; Kuchar *et al.*, 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of the Hunga Tonga eruption on the planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1- 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the recent trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and for the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe *et al.* 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold,” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC

also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first columns Table 12.12 in Ranasinghe *et al.* (2021, p. 1856), reproduced here as Table 8.1, summarize the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Out of the 33 weather impact categories listed, an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence* assertions, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Further, two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, or drought.

Other columns of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here: whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer and Stevens 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan et al, 2019). Even with these caveats, we note that the omitted columns in AR6 Table 12.12 show most weather impacts are not expected to exhibit an anthropogenic signal through the end of this century.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	4
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fire weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	11
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

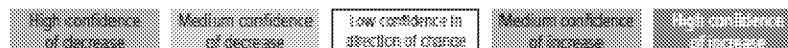


Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

As discussed in Chapter 6 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that it is not currently possible to attribute changes in most extreme weather types to human influences. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.6 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between its chapters. Chapter 11 of WG1 states (Seneviratne *et al.*, 2021):

Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.

By contrast, as noted in Section 8.5, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare an event in today's climate with one in a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100 percent of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.

Because EEA is relatively new, many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the U.S. National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 6, many of the worst extreme weather and climate events in U.S. history occurred in the first half of the 20th century, including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass thresholds of what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean that a climate change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an “ordinary” weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second “heatwave” regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh *et al.* (2015) both point out that different distributions might fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis, drawing a connection between individual events and global climate change should be avoided. Furthermore, the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow *et al.*, 2020). Methods to eliminate the bias have not yet been established, leading some experts (*e.g.* Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain that it should be avoided altogether.

We provide a case study of a recent high impact extreme event in the U.S. to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.6.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme event that affected much of Western North America in late June 2021. Surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass *et al.*, 2024).

The WWA team generated international headlines with their analysis, which provided the following attribution statements (WWA, 2021; Philip *et al.*, 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a one in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important counter to the first claim is that other researchers concluded from historical weather data that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman, 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman, 2023, p. 49).

Mass *et al.* (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking mid-tropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking mid-tropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass *et al.* assessed that there was no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming might have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

Bercos-Hickey *et al.* (2022) conducted a statistical analysis of a model-based attribution study of this heat wave. Because the event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave - they provided a more highly constrained estimate that human activities caused a ~1.4°F–1.8°F increase in the daily maximum temperatures.

Zeder *et al.* (2023) also concluded that the methods employed by Philip *et al.* (2022, the WWA analysis) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analyses showed that the event was caused by rare meteorological conditions that were not made more probable by global warming.

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PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

9 CLIMATE CHANGE AND U.S. AGRICULTURE

Chapter summary

There has been abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. The increase in ambient CO₂ has also boosted productivity of all major U.S. crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from, or be harmed by, climate change, once the adaptive responses of farmers are considered the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn *et al.* (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn *et al.* method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached conclusions similar to Mendelsohn *et al.* (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the U.S. agricultural sector. However, a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in U.S. agriculture due to climate warming.

Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and

20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2, CO₂ is a major driver of plant growth, so this omission biases the analysis towards underestimation of the benefits of climate change to agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiments” or FACE plots, in which small sources of CO₂ are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth *et al.* (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm caused an average 18 percent increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key U.S. agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations improved photosynthesis rate, water use efficiency, and growth Li (2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. There were also ten studies reporting on +600 ppm CO₂ enrichment, which increased photosynthesis by an average of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr., 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41 percent loss of growth under ambient CO₂ but only a 13 percent loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured both the yield and nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16 percent but a 7 percent decrease in grain protein levels. But they also found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection, growers could select wheat types that best take advantage of the elevated CO₂.

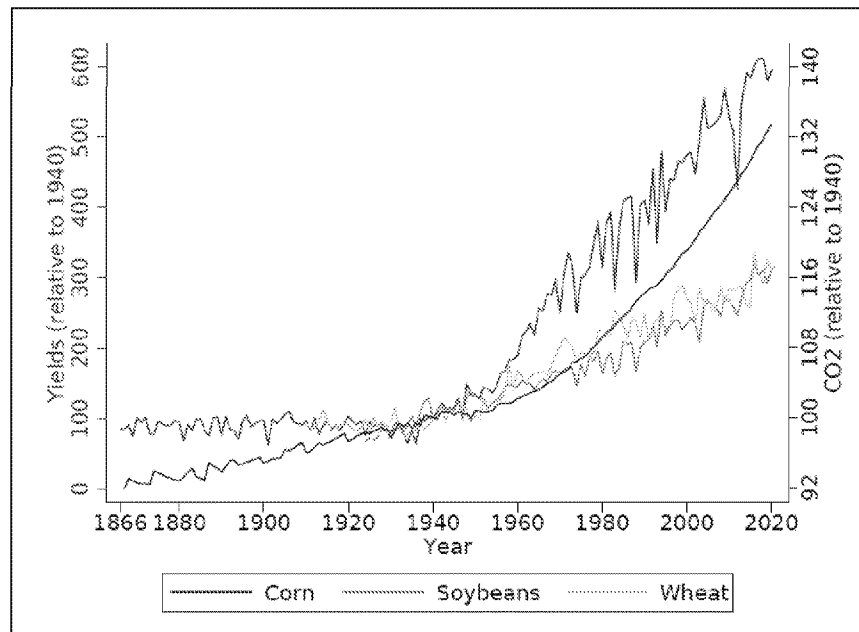


Figure 9.1: U.S. average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100. Source: Taylor and Schlenker (2021)

Further evidence

A 2021 report from the U.S. National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted U.S. crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

Beyond growth benefits, extra CO₂ boosts plant resilience to dryness. Deryng *et al.* (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for maize (corn), wheat, rice and soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them; once fertilization was taken into account, all regions showed a net CWP gain. Deryng *et al.* also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains and mitigated by up to 90 percent for rice and 60 percent for maize. Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng *et al.* (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, observations show the opposite: greening is happening even in arid areas. Zhang *et al.* (2024) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4 percent of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the U.S. Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based largely on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore *et al.*, 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore *et al.* (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore *et al.* projected declining global crop yields for all crop types in all regions due to warming.

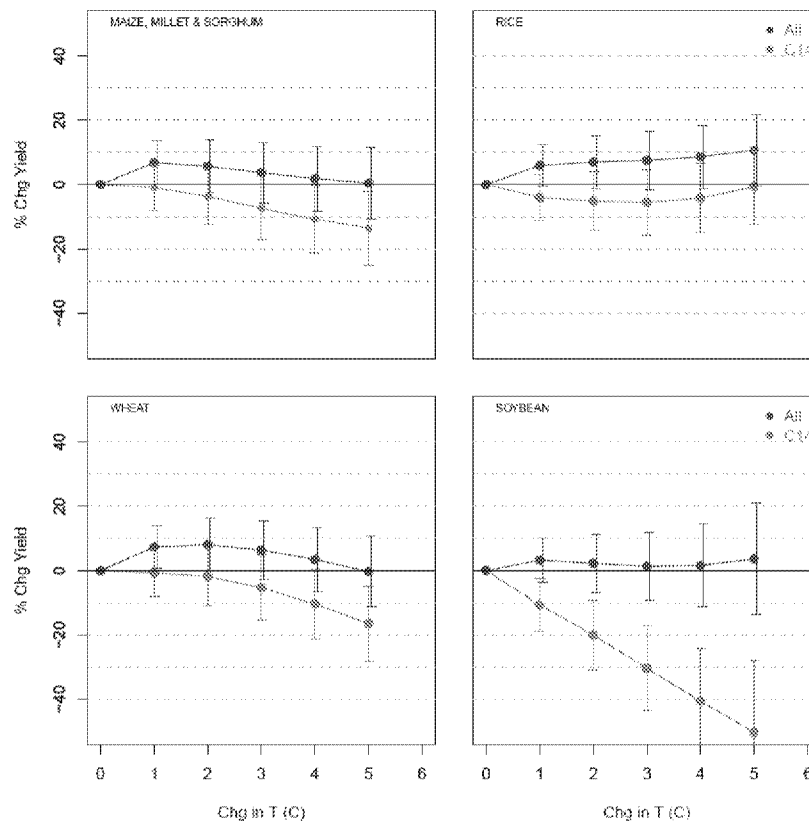


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore *et al.* (2017). Green: after including omitted data. Source: McKittrick (2025).

McKittrick (2025) re-examined the Moore *et al.* database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the records most commonly missing were the changes in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables, thereby increasing the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 9.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

9.4 CO₂ fertilization and nutrient loss

Evidence has shown that CO₂-induced biomass gains are sometimes accompanied by reductions in the concentrations of protein and other key nutrients such as iron and zinc (Ebi *et al.* 2021). Some experimental evidence has shown that the rising temperatures expected to accompany higher CO₂ levels will offset this loss (Köhler *et al.* 2019) although the evidence for this is mixed, as is the evidence that nutrient dilution observed to date is attributable to higher CO₂ (Ziska 2022). If nutrient dilution does occur under rising CO₂ levels there are several adaptive strategies that could be pursued.

First, selective breeding to raise micronutrient content is already long established (Saltzman *et al.* 2017) and has proven to be a cost-effective agronomic strategy (Ebi *et al.* 2021). Strategies can include both conventional breeding and genetically-modified organisms. An example of the latter is Golden Rice, which contains elevated levels of beta-carotene to boost biosynthesis of vitamin A in the human body. Optimal strategies will be location-specific because they vary by crop, climate and soil type (Ebi *et al.* 2021). Second, fortification of food products with micronutrients is already routine. Folic acid (a B vitamin) is added to flour and many other foods; iodine is added to table salt, most commercial breakfast cereals are fortified with iron and numerous vitamins, *etc.* Third, dietary supplements in the form of multivitamin tablets are inexpensive, widely-available and routinely consumed.

One concern about reliance on adaptive strategies is whether they are feasible in low-income countries. Micronutrient deficiency is already a problem in the developing world and dietary supplements have proven to be an effective low-cost response (Ebi *et al.* 2021). It should also be noted the IPCC emission scenarios that generate high levels of warming do so on the basis of high levels of income growth. The SSP scenarios³ assume that, compared to 2005 levels, global per capita income will double by 2100 in the lowest growth case (SSP3), and in the highest emission case (SSP5) global per-capita income will grow nearly 16-fold. In that scenario even the poorest regions (Africa and the Middle East) end up with a per capita income of about US\$126,000, 70 percent higher than current U.S. per capita income (about US\$75,000). Consequently the same scenarios in which CO₂ levels increase the most are also those in which global poverty is largely eliminated, in which case all countries would be able to afford dietary supplements as necessary to address micronutrient deficiencies, if they arise and cannot be addressed using on-farm agricultural strategies.

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to U.S. agriculture. To the extent nutrient dilution occurs there are mitigating strategies available that will need to be researched and adapted to local conditions.

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³ See compilation at [[HYPERLINK "https://ourworldindata.org/explorers/ipcc-scenarios?Metric=GDP&Sub-metric=Total+radiative+forcing&Region=Global&country=SSP1+-+Baseline~SSP2+-+Baseline~SSP3+-+Baseline~SSP4+-+Baseline~SSP5+-+Baseline"](https://ourworldindata.org/explorers/ipcc-scenarios?Metric=GDP&Sub-metric=Total+radiative+forcing&Region=Global&country=SSP1+-+Baseline~SSP2+-+Baseline~SSP3+-+Baseline~SSP4+-+Baseline~SSP5+-+Baseline)].

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10 MANAGING RISKS OF EXTREME WEATHER

Chapter summary

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The U.S. economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase if people are able to undertake adaptive responses.

10.1 Socioeconomic context

Risks from human-caused climate change are affected by natural weather and climate variability and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as U.S. population grew from 76 million in 1900 to over 331 million in 2020 (Goklany 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01 percent of the U.S. population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006 percent of the U.S. population) (NOAA National Hurricane Center 2025; U.S. Census Bureau 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang 2023). U.S. weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (Molina and Rudik 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992), have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (Battelle Memorial Institute 2013). Inland dams in the U.S. help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During

Hurricane Helene (2024), TVA’s strategies prevented approximately \$406M in potential damages (APPA 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1 Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the U.S., so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster as a proportion of GDP have decreased by about 80 percent since 1980, as shown in Figure 10.1. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments, NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (Pielke Jr., 2025).

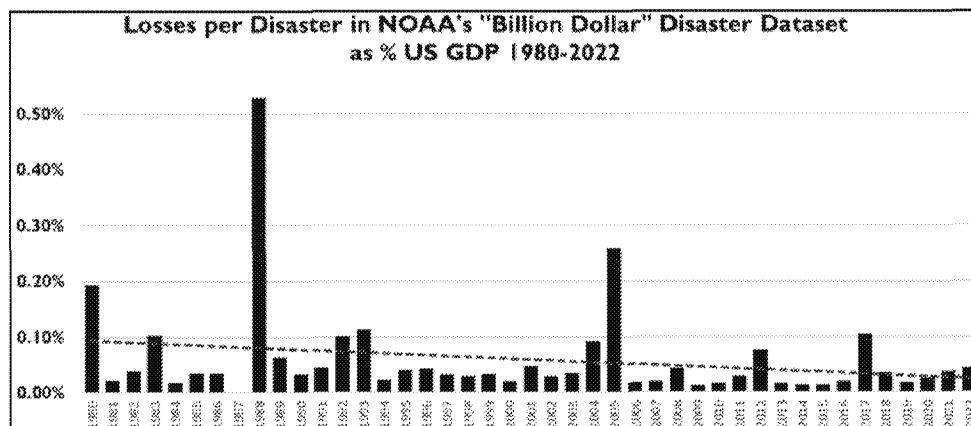


Figure 10.1: Losses per disaster as a % of Gross Domestic Product in NOAA’s billion-dollar disaster dataset (the version downloaded in July 2023), 1980 to 2022. Source: (Pielke, Jr. 2024)

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. Finally, the U.S. economy’s expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period, though not in the continental U.S. (Chapter 6), and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes typically stems from hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 2024). Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini *et al.* 2015, Lee and Dessler 2023). The U.S. EPA (citing data from the Centers for Disease Control) reports that on average over 1999 to 2015 there were 2.2 deaths per million Americans for which cold was listed as the main underlying cause and an additional 2.4 deaths per million for which cold was listed as a contributing factor (EPA 2025). By contrast there were 1.3 deaths per million for which heat was the main cause and an additional 0.8 per million for which it was a contributor. By this metric cold accounts for approximately double the weather-related deaths as does heat.

Epidemiological methods that consider correlational evidence, not just death certificate reports, indicate the cold/warm ratio might be much higher. A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7 percent of deaths were attributable to sub-optimal temperatures, of which 7.4 percent were attributable to cold and only 0.4 percent were attributable to heat (Gasparini *et al.* 2015). In other words, cold weather killed 18.5 times as many people as did hot weather.

Figure 10.2 shows the distribution of results from Gasparini *et al.* (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9 percent, of which 5.5 percent was due to cold, thus cold weather killed 14 times as many people as hot weather.

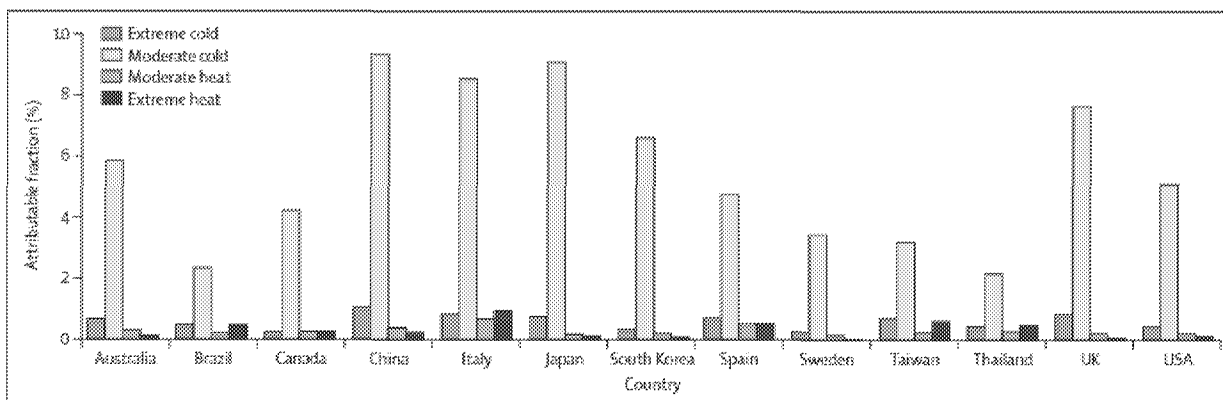


Figure 10.2. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini *et al.* (2015).

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86 percent of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis *et al.* (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb *et al.* (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60 percent decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio *et al.* (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, rising temperatures are associated with a net saving of lives since they reduce mortality from cold events. The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill *et al.* 2022) acknowledges that heat-related mortality risk is declining over time:

Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.

Yet the IPCC misrepresents the overall situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

The observed decline in U.S. heat-related mortality has been specifically attributed to adaptation. Wang *et al.* (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live, Wang *et al.* (2018) project not only no increase in heat-related mortality, but an overall mortality *decrease* for the U.S. as a whole. They conclude that

Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.

10.3.2 Mortality risks and energy costs

A 2016 study of U.S. long term mortality risks associated with temperature variations (Barreca *et al.* 2016) showed that increases in mortality across the U.S. are associated with both cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus *et al.* (2022) showed that wealthy and poor households in the U.S. adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($> 30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

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11 CLIMATE CHANGE, THE ECONOMY, AND THE SOCIAL COST OF CARBON

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in AR5. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy and that trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries, but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points does not justify major revisions to SCC estimates.

11.1 Climate change and economic growth

11.1.1 Overview

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus, 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued

that any effects of climate change on U.S. economic activity would be small relative to the many other changes that would happen (Schelling 1992).

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report (Arent *et al.* 2014, emphasis added)

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

Evidence since AR5 does not change this assessment. Mohaddes *et al.* (2023) found that warm weather shocks have small negative effects on U.S. state-level output but not income, while cold weather shocks negatively affect both and the impacts are about four times larger, implying a shift to warmer conditions would, if anything, yield a net economic benefit for the U.S.

These statements are validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty.

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen, 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr, 2018, 2020) as have mortality risks (Formetta and Feyen, 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick, 2015). Nor have past extreme weather events had a significant effect on U.S. banks' performance (Blickle *et al.*, 2021); warming has even been shown to be beneficial for the finance and

insurance sector (Mohaddes *et al.* 2023). Figure 11.1 below is illustrative. For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it (Storm 2017):

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

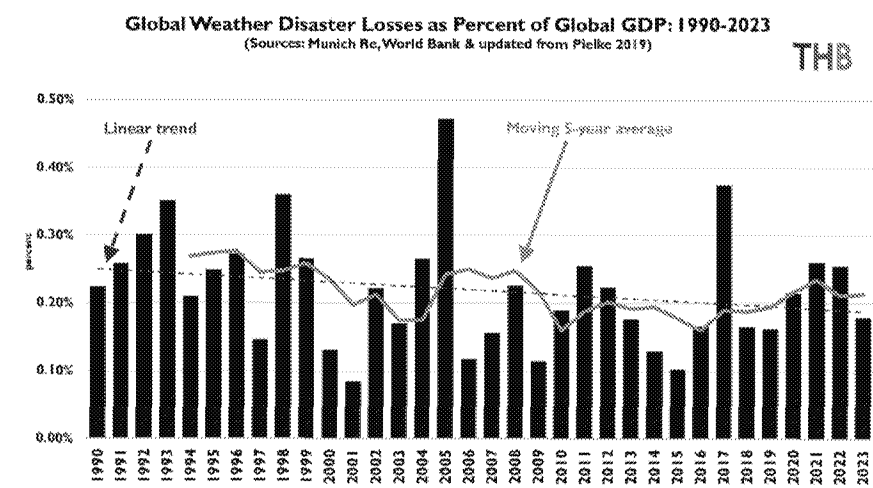


Figure 11.1 Global weather losses as a fraction of GDP. Source: Pielke Jr. (2023)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future, 2025). Nordhaus’ work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus, 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus’ Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of

DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we modestly scale back fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even more costly.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

11.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell *et al.* (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke *et al.* (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao *et al.* (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer *et al.* (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang *et al.* (2023) updated the DJO12 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell *et al.* (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke *et al.* (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke *et al.* (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95 percent confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans –86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is considered the original temperature effects reported by Dell *et al.* became small and insignificant.

Berg *et al.* (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall, they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100, even using the extreme RCP8.5 scenario, they computed the average global GDP loss would be only 1.9 percent compared to a scenario with no warming. That is, instead of the economy growing 400 percent it would grow 392%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 392 percent growth.

To summarize, economists consider climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming might have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust (Tol 2024). Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

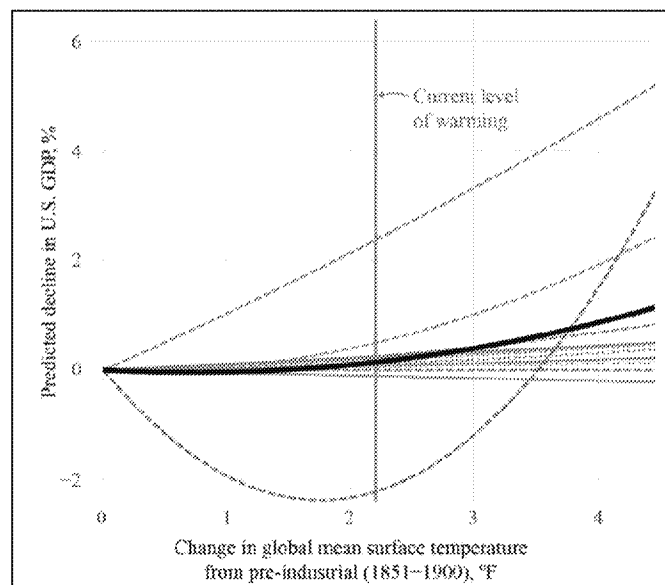


Figure 11.2: Decline in U.S. GDP per degree of warming. Source: CEA-OMB (2023)

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. Figure 11.2, from a 2023 CEA-OMB report, shows the expected decrement in U.S. GDP as a

function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe on the U.S. GDP is indeed negligible.

11.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

11.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many, if not most, of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with a changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordhaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0 percent GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5 percent for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past

hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this might fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

11.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. The most recent data-driven ECS values tend to be lower than this (see Chapter 4). Dayaratna *et al.* (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 9) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg *et al.* 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.

- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the U.S. Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore *et al.* (2017). But as discussed in Chapter 9, McKittrick (2025) showed that Moore *et al.* (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA’s SCC revision attributable to agricultural yield losses was unwarranted.

11.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 9 looked at climate change and U.S. agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. Haverd *et al.* (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna *et al.* (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF⁴ value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle, 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

11.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon

⁴ Marginal Cost of Public Funds: the optimal carbon tax rate is the SCC divided by the MCPF (Sandmo 1977).

(SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz *et al.*, 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example, an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford, 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example, a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen *et al.* 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford, 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the second type is a possibility. Kypke *et al.* (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon, 2023).

The possible existence of bifurcations in the Earth’s climate system implies abrupt transitions are possible, not just in response to large forcing but also to small perturbations. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos *et al.*, 2024) and indeed might not be able to since one implication of the “butterfly effect” is the existence of predictability boundaries of nonlinear systems (Palmer *et al.*, 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict it or prevent it from happening.

AR6 (WGI, Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the “tipping point” concept in discussions of climate change (see [[HYPERLINK "https://report-2023.global-tipping-points.org/what-is-a-tipping-point/"](https://report-2023.global-tipping-points.org/what-is-a-tipping-point/)] for example). As summarized by AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton *et al.*, 2023). It identifies more than 25 parts of the

climate system said to constitute tipping points. What gets classified as a climate “tipping point” is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of parts of the Greenland and West Antarctic ice sheets. These impacts can reverse on the decadal and century timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). AR6 WG1 Summary for Policy Makers states:

The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is *high confidence* in the 21st century decline, there is only *low confidence* in the magnitude of the trend. There is *medium confidence* that there will not be an abrupt collapse before 2100. (C.3.4)

There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5). (B.5.2)

For the purpose of SCC calculations, the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz *et al.* incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However, the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there might be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been considered, the result is only a modest increase in the SCC value in the 21st century.

11.2.5 Are there alternatives?

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung, 2017) stated it’s “time to kill it” due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for “target-consistent” carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However, the uncertainty of SCC estimates doesn’t mean that other regulatory measures are inherently better or more efficient. Many emissions regulations (such as

electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) cost far more per tonne of abatement than any mainstream SCC estimate, which is sufficient to establish that they fail a cost-benefit test.

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12 GLOBAL CLIMATE IMPACTS OF U.S. EMISSIONS POLICIES

Chapter Summary

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

12.1 The scale problem

The emissions rates and atmospheric concentrations of criteria air contaminants are closely connected because their lifetimes are short and their concentrations are small; when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since emissions mix globally and the global carbon cycle is vast and slow. Any change in local CO₂ emissions today will have only a very small global effect, and only with a long delay.

Following the emission of a pulse (release) of CO₂ into the atmosphere only about 40±15 percent of the extra CO₂ will have been sequestered after twenty years. That fraction rises to 75±10 percent after a thousand years, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais *et al.*, 2013, pp. 472-473). Consequently, any reduction in U.S. emissions would only modestly slow, but not prevent, the rise of global CO₂ concentration. And even if global emissions were to stop tomorrow, it would take decades or centuries to see a meaningful reduction in the global CO₂ concentration and hence human influences on the climate.

Reducing the atmospheric stock of CO₂ would require emissions to fall below the natural sequestration rate, assuming the entire increase is anthropogenic. Since that rate has been averaging about 50 percent of emissions in recent decades, a reduction of global emissions by 50 percent would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy was too difficult for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley, 1998). Lomborg (2016) estimated that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions will have negligible local effects, and only with a long delay. The practice of referring to unilateral U.S. reductions as “combatting climate change” or “taking action on climate” therefore reflects a profound misunderstanding of the scale of the issue.

12.2 Case study: U.S. motor vehicle emissions

The scale problem can be illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. The 2009 Endangerment Finding therefore obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the U.S. public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing U.S. vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to the reduction in global emissions, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0 percent of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating *all* U.S. vehicle-based emissions would retard the accumulation of CO₂ in the atmosphere by a year or two over a century.

It would also reduce the overall warming trend by at most about 3 percent. For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends are determined to a precision of about ± 15 percent, so the impact of reducing the rate of global warming by eliminating U.S. vehicle CO₂ emissions would be far below the limits of measurability. Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, in contrast to the case of local air contaminants like particulates and ozone, even the most aggressive regulatory actions on GHG emissions from U.S. vehicles cannot be expected to remediate alleged climate dangers to the U.S. public on any measurable scale.

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GLOSSARY

2XCO₂: Doubling of the atmospheric carbon dioxide (CO₂), a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50 percent of the way to 2XCO₂ compared to 1800.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

ACRIM (Active Cavity Radiometer Irradiance Monitor) GAP: the gap in total solar irradiance data between 1989 and 1991 caused by a delay in the launch of a satellite-borne monitor in time to overlap and intercalibrate with the prior system.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The “opposite” of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

AMO: Atlantic Multidecadal Oscillation, a 60-year cycle of sea surface temperatures in the North Atlantic.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science and the others concerned with societal impacts and mitigation strategies. The most recent was AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CLIMATE CHANGE: A change in climate due to human influences, as opposed to climate variability which is natural in origin.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyse economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens of a country, including exports and imports, usually over one year.

GDP (Gross National Product): Total market value of all the domestically-produced final goods and services produced by the citizens of a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PDO: Pacific Decadal Oscillation, a recurring ocean-atmosphere interaction centered over the Pacific basin associated with predominantly warm or cool patterns that influence the global climate.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TONNE: Metric ton.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

TSI (Total Solar Irradiance): The measure of the total amount of incident solar radiation per unit area, including all wavelengths of electromagnetic radiation, that reaches the Earth's atmosphere. Typically shown in units of watts per square meter (W/m²).

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

METADATA FOR FIGURES AND TABLES

Figure 2.1 Screen shot from Figure 3 of Zhu *et al.* 2016 [HYPERLINK "<https://www.nature.com/articles/nclimate3004>"]

Figure 2.2 Data replotted from Berner 2006 Figure 18, with annotation in red added by authors [HYPERLINK "<https://www.sciencedirect.com/science/article/pii/S0016703706002031>"]

Figure 2.3 Screen shot from Gerhart and Ward (2010) Figure 2 [HYPERLINK "<https://nph.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8137.2010.03441.x>"]

Figure 2.4 Screenshot from Copernicus Marine Services [HYPERLINK "https://data.marine.copernicus.eu/product/GLOBAL_OMI_HEALTH_carbon_ph_area_averaged/description"]

Figure 2.5 Screen shot from AIMS (2023) Figures 2-4 [HYPERLINK "https://www.aims.gov.au/sites/default/files/2022-08/AIMS_LTMP_Report_on%20GBR_coral_status_2021_2022_040822F3.pdf"]

Figure 3.1.1 Screen shot of AR6 WG1 Ch2 Fig 10

Figure 3.1.2 Screen shot of AR6 WG1 Ch7 Fig 7-6

Figure 3.1.3 Author created figure. CO2 data source: [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]

Figure 3.2.1 Screen shot from Hausfather *et al.* (2019) Figure S4 [HYPERLINK "<https://doi.org/10.1029/2019GL085378>"]

Figure 3.2.2 Author created figure. Data source: Freidlingstein *et al.* (2024) [HYPERLINK "<https://essd.copernicus.org/preprints/essd-2024-519>"]
Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 3.2.3 Author-created using OLS trends, Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 3.2.4 Author-created using OLS trends, Data source: [HYPERLINK "<https://globalcarbonbudget.org/download/1442/>"]

Figure 4.1 Screen shot from Scafetta (2021) Figure 1 [HYPERLINK "<https://doi.org/10.3390/cli9110161>"]

Figure 5.1 Data source: [HYPERLINK "<https://climexp.knmi.nl/start.cgi>"]. Author-created figure. One ensemble member per model, yearly average temperatures are computed from the global monthly raw temperatures; ‘range’ is the warmest model temperature minus the coolest model temperature in each year; standard deviation computed across all 33 models’ raw temperatures in each year.

Figure 5.2 Screen shot from Scafetta (2023) Figure 2 [HYPERLINK "<https://doi.org/10.1007/s00382-022-06493-w>"]

Figure 5.3 Author created figure. Data source: [[HYPERLINK "https://climexp.knmi.nl/start.cgi"](https://climexp.knmi.nl/start.cgi)]. One SSP370 ensemble member per model. Linear OLS trends computed from global monthly temperature anomalies relative to 1981-2010.

Figure 5.4 Author created figure, based on Figure 3 of McKittrick and Christy (2020) [[HYPERLINK "https://doi.org/10.1029/2020EA001281"](https://doi.org/10.1029/2020EA001281)]. Updated using same methods and data extended from 2014 to 2024, see McKittrick and Christy (2025) in chapter references.

Figure 5.6 Screen shot of IPCC AR5 Figure 10.SM1, with author annotations

Figure 5.7 Author created figure following Christy and McNider (2017) [[HYPERLINK "https://doi.org/10.1007/s13143-017-0070-z"](https://doi.org/10.1007/s13143-017-0070-z)] with updated data available at [[HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/ERA5_REANALYSES/"](https://www.nsstc.uah.edu/data/cmip6/ERA5_REANALYSES/)] and [[HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/JRA3Q_REANALYSES/"](https://www.nsstc.uah.edu/data/cmip6/JRA3Q_REANALYSES/)] compiled here [[HYPERLINK "https://www.nsstc.uah.edu/data/cmip6/CWG25_Fig_5.7_Table_250627.xlsx"](https://www.nsstc.uah.edu/data/cmip6/CWG25_Fig_5.7_Table_250627.xlsx)]

Figure 5.8 Screen shot from [[HYPERLINK "https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"](https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1)] (accessed May 27, 2025)

Figure 5.9 Screen shot from Rugenstein and Hakuba (2023) Figure 1 [[HYPERLINK "https://doi.org/10.1029/2022GL101802"](https://doi.org/10.1029/2022GL101802)]

Figure 5.10 Author created figure. Data source [[HYPERLINK "https://climexp.knmi.nl/start.cgi"](https://climexp.knmi.nl/start.cgi)]. OLS linear trends. One SSP370 ensemble member per model, averaged surface air temperatures for June through August over 31N to 49N latitude, 84W to 102W longitude. Observed temperature data for same months from NOAA/NCEI at <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series> for the 12 Corn Belt states averaged together.

Figure 6.1.1 Author replot of Figure 10 from Koutsoyiannis (2013) [[HYPERLINK "http://dx.doi.org/10.1080/02626667.2013.804626"](http://dx.doi.org/10.1080/02626667.2013.804626)]

Figure 6.2.1 Screen shot of figure from Maue (2025) [[HYPERLINK "https://climatlas.com/tropical/"](https://climatlas.com/tropical/)]

Figure 6.2.2 Author created figure. Data from National Hurricane Center (2024) [[HYPERLINK "https://www.nhc.noaa.gov/climo/"](https://www.nhc.noaa.gov/climo/)]

Figure 6.2.3 Author created figure. Data from NOAA HRD [[HYPERLINK "https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html"](https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html) \t "_new"]

Table 6.2.1 Author created table. Data from NOAA HRD [[HYPERLINK "https://www.aoml.noaa.gov/hrd/hurdat/most_intense.html"](https://www.aoml.noaa.gov/hrd/hurdat/most_intense.html) \t "_new"]

Figure 6.3.1 Screen shot from NCA4 Figure 6.4

Figure 6.3.2 Author created figure. Data source: [[HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"](https://www.nsstc.uah.edu/data/ushcn_jrc/)]

Figure 6.3.3 Author created figure. Data source: [[HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"](https://www.nsstc.uah.edu/data/ushcn_jrc/)]

Figure 6.3.4 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.5 Author created figure Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.6 Author created figure. Data source: [HYPERLINK "https://www.nsstc.uah.edu/data/ushcn_jrc/"]

Figure 6.3.7 Screen shot from [HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"]

Box tables. Author created table. Data from McKittrick and Christy (2025)

Figure 6.4.1 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.2 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.3 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.4 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.4.5 Author created figure. Data from McKittrick and Christy (2025)

Figure 6.5.1 Author created figure. Data source: [HYPERLINK "https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv"]

Figure 6.7.1 Author created figure. Data source: [HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"] accessed June 16, 2025. OLS trend line added.

Figure 6.8.1 Screen shot from Lizundia-Loiola *et al.* (2021) Figure 12.

Figure 6.8.2 Screenshot from Marlon *et al.* (2012) Figure 2 panel C.
[HYPERLINK "https://www.pnas.org/doi/pdf/10.1073/pnas.1112839109"]

Figure 6.8.3 Author created Figure. Data 1926 to 2016: [HYPERLINK "https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html"]. Post-2017 [HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"] Accessed June 16, 2025.

Figure 7.1 Screenshot from [HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/"]

Table 7.1 Author created table. From Section 6.2 of
[HYPERLINK "https://judithcurry.com/wp-content/uploads/2018/11/special-report-sea-level-rise-3.pdf"]

Figure 7.2 Screenshot from [HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290"] (downloaded 4/22/25)

Figure 7.3 Screenshot from

[HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450"]
(downloaded 4/22/2025)

Figure 7.4 Screenshot from

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(downloaded 4/22/25)

Figure 7.5 Screenshot from

[HYPERLINK "https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750"]
(downloaded 4/22/25)

Figure 7.6 Author created figure. Data from [HYPERLINK

"https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750"]

Figure 8.1 Screenshot from

[HYPERLINK "<https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf>"]

Figure 8.2 Screenshot from Hansen and Karecha (2025) Figure 1

[HYPERLINK "<https://www.columbia.edu/~jeh1/mailings/2025/CloudFeedback.13May2025.pdf>"]

Table 8.1 Screenshot of column 1 of Table 12.12 IPCC AR6 Working Group I report

Figure 9.1 Screenshot From Taylor and Schlenker (2021) Figure 1

[HYPERLINK "<https://www.nber.org/papers/w29320>"]

Figure 9.2 Screenshot from McKittrick (2025) Figure 1

[HYPERLINK "<https://www.nature.com/articles/s41598-025-90254-2>"]

Figure 10.1 Screenshot from Pielke (2024) [HYPERLINK "<https://www.nature.com/articles/s44304-024-00011-0>"] Figure 3.

Figure 10.2 Screenshot from Gasparini *et al.* (2015) Figure 2

[HYPERLINK "[http://dx.doi.org/10.1016/S0140-6736\(14\)62114-0](http://dx.doi.org/10.1016/S0140-6736(14)62114-0)"]

Figure 11.1 Screen shot from Pielke Jr (2023)

[HYPERLINK "<https://rogerpielkejr.substack.com/p/global-disaster-losses1990-2023>"]

Figure 11.2 Screenshot from CEA-OMB (2023) [HYPERLINK

"<https://bidenwhitehouse.archives.gov/wp-content/uploads/2023/03/CEA-OMB-White-Paper.pdf>"]
Figure 1.

ABOUT THE AUTHORS

John Christy, Ph.D. is the Distinguished Professor of Atmospheric and Earth Sciences and Alabama's State Climatologist at the University of Alabama in Huntsville. He has a B.A. (Mathematics) from CSU Fresno and an M.S. and Ph.D. (Atmospheric Sciences) from the University of Illinois in Urbana-Champaign. He is a Fellow of the American Meteorological Society and recipient of The NASA Medal for Exceptional Scientific Achievement for constructing, with Dr. Roy Spencer, the first global atmospheric temperature dataset from polar orbiting satellites. He served as Lead Author of the 3rd IPCC Assessment Report (2001), he coauthored the National Academy of Science expert report on Surface Temperature Reconstructions (2006), and he has served on the NOAA Climate Change Science Program, NASA's Earth Science Subcommittee, the National Research Council Space Studies Board and the EPA Science Advisory Board. In addition, Dr. Christy has given testimony in 20 Congressional Hearings.

Judith Curry, Ph.D. is Professor Emerita at the Georgia Institute of Technology, where she served as Chair of Earth and Atmospheric Sciences for 13 years. She is President and co-founder of Climate Forecast Applications Network (CFAN). Curry has a PhD in Geophysical Sciences from the University of Chicago. She has authored or coauthored 192 peer-reviewed papers in atmospheric and climate sciences, two textbooks, and most recently the book *Climate Uncertainty and Risk*. Curry is a Fellow of the American Meteorological Society, the American Association for the Advancement of Science, American Geophysical Union, and a Member of the American Academy of Sciences and Letters. She has served on several Science Steering Committees of the World Climate Research Program and also the DOE Biological & Environmental Research Advisory Committee, Earth Science Subcommittee of the NASA Advisory Council, and the NRC Space Studies Board and Climate Research Committee. Dr. Curry has given testimony in 13 Congressional Hearings..

The Honorable Steven E. Koonin, Ph.D. is the Edward Teller Senior Fellow at Stanford's Hoover Institution. He has served as Under Secretary for Science at the Department of Energy (2009-2011), as Chief Scientist for British Petroleum (2004-2009), and as a professor at Caltech (1975 – 2004, the last nine years as Vice President and Provost). Koonin is a member of the National Academy of Sciences and the JASON group of government advisors, as well as a Governor of Lawrence Livermore National Laboratory, having served in similar capacities for the Los Alamos, Sandia, Brookhaven, and Argonne National Laboratories. Other prior roles include a University Professor at New York University, a non-resident Senior Fellow at the American Enterprise Institute, and a Trustee of the Institute for Defense Analyses. Koonin has a BS in Physics from Caltech and a PhD in Theoretical Physics from Massachusetts Institute of Technology. He authored the 2021 bestseller *Unsettled: What Climate Science Tells Us, What It Doesn't, and Why It Matters*, the 1985 textbook *Computational Physics*, and some 200 peer-reviewed papers in physics and astrophysics, scientific computation, energy technology and policy, and climate science.

Ross McKittrick, Ph.D., is a Professor of Environmental Economics at the University of Guelph in Ontario, Canada. He holds a BA in economics from Queen's University, and an MA and Ph.D. in economics from the University of British Columbia. He has published widely in both economics and physical science journals on topics related to climate change, pollution and public policy. His book *Economic Analysis of Environmental Policy* was published by the University of Toronto Press in 2010. His background in applied statistics has led him to author or coauthor peer-reviewed publications across a wide range of topics in the physical sciences including paleoclimate reconstruction, malaria transmission, surface temperature measurement, climate attribution methodology and climate model evaluation. Professor McKittrick has made many invited academic presentations around the world, was an invited contributor to the 2006

National Academy of Sciences report on Surface Temperature Reconstructions, has served as an expert reviewer for the last three IPCC Assessment Reports (Working Groups I and II) and has testified before the U.S. Congress and committees of the Canadian House of Commons and Senate.

Roy W. Spencer, Ph.D., is a Principal Research Scientist at the University of Alabama in Huntsville. He holds a BS in Atmospheric and Oceanic Science from the University of Michigan, and MS and PhD in Meteorology from the University of Wisconsin -Madison. Spencer's published research has focused on monitoring of weather processes and climate change from Earth-orbiting satellites, as well as using simple physical models for diagnosing climate sensitivity and climate feedbacks. As a NASA Senior Scientist for Climate Studies he served as the U.S. Science Team Leader for the Advanced Microwave Scanning Radiometer (AMSR-E) flying on the Aqua satellite, providing our most accurate global measurements of sea surface temperatures, sea ice, and several other features of the climate system. Along with Dr. John Christy, Spencer developed the first satellite-based technique for global temperature monitoring, for which they received NASA's Exceptional Scientific Achievement Medal and the American Meteorological Society's Special Award.

From: Judith Curry <curry.judith@gmail.com>
Sent: Monday, May 19, 2025 7:30 PM
To: Ross McKittrick; Steve Koonin; John Christy; Roy Spencer; Travis Fisher
Subject: Albedo text for ch 5
Attachments: Hemispheric symmetry of the planetary albedo.docx

Attached

--



Judith Curry, President
CFAN - Climate Forecast Applications Network
Reno, NV USA
curry.judith@cfanclimate.com | +1.404.803.2012
<http://www.cfanclimate.net>

5.8 Hemispheric symmetry of the planetary albedo

The planetary albedo is the portion of solar radiation reflected by the planet back to space, and is an important determinant of whether the planet will warm or cool over time. An intriguing property of the planetary albedo is that, on average, Northern Hemisphere (NH) and Southern Hemisphere (SH) have the same albedo (Stephens et al., 2015). The hemispheric symmetry is at least robust throughout the satellite record (since the 1970s). The symmetry of the hemispheric albedo is surprising, because SH has much more ocean than land, and ocean is less reflective than land, so the NH should have higher albedo. Clouds (which are highly reflective) compensate the surface albedo imbalances of the two hemispheres, leading to an overall symmetric albedo between the hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH.

While the reasons for this hemispheric symmetry in albedo are unclear, its mechanism likely operates on large temporal and spatial scales. The existence of this symmetry is a useful metric for evaluating climate models. Rugenstein and Hakuba (2023) evaluate the hemispheric albedo for the CMIP6 climate model simulations. Albedo asymmetry is defined by the NH minus the SH the Northern Hemisphere (NH) minus Southern Hemisphere (SH) difference in annual mean hemispheric albedo. The observed asymmetry is small, about 0.1 W m^{-2} . Figure 5.8.1 shows that the observed hemispheric symmetry of reflected flux is not reproduced by most of the CMIP6 models, and there is disagreement between models as to which hemisphere is more reflective. The magnitude of the asymmetry in some of the models is very large, compared both to the observed value and to current human influences (about 2.5 W m^{-2}).

The significance of this discrepancy between climate models and observations of the hemispheric albedo symmetry is not yet fully known. However, model studies suggest that interhemispheric changes in albedo can alter the amount of heat moved poleward, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy further raises issues regarding cloud feedback processes and their magnitude.

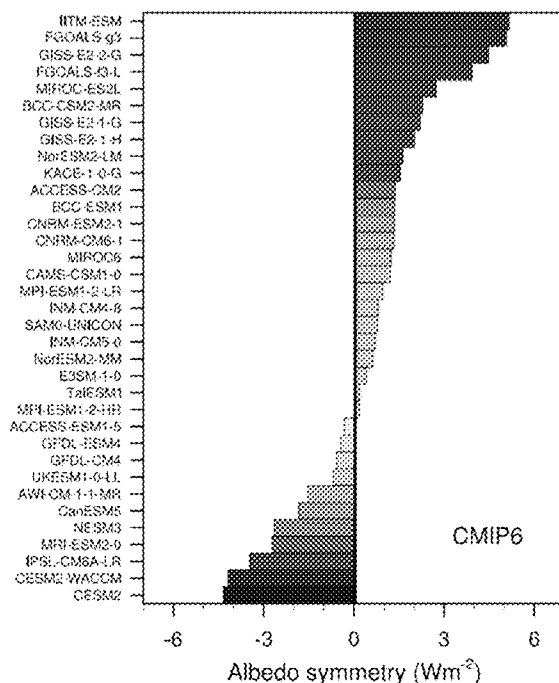


Figure 5.8.1 Differences in the reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

Rugenstein, M., & Hakuba, M. (2023). Connecting hemispheric asymmetries of planetary albedo and surface temperature. *Geophysical Research Letters*, 50, e2022GL101802.

Datseris, G., & Stevens, B. (2021). Earth's albedo and its symmetry. *AGU Advances*, 2, e2021AV000440. [https:// doi.org/10.1029/2021AV000440](https://doi.org/10.1029/2021AV000440)

Stephens, GL, D O'Brian, PJ Webster et al (2015) The albedo of Earth. *Reviews of Geophysics*.

From: Roy Spencer [roywspencer@hotmail.com]
Sent: 5/22/2025 12:15:40 PM
To: Steven Koonin [steven.koonin@gmail.com]; 'John Christy' [climateman60@gmail.com]; 'Ross McKittrick' [ross.mckittrick@gmail.com]; 'Judith Curry' [curry.judith@gmail.com]; 'Travis Fisher' [travis.scott.fisher@gmail.com]
Subject: and here's the replacement for Fig. 5.3...
Attachments: paste.png

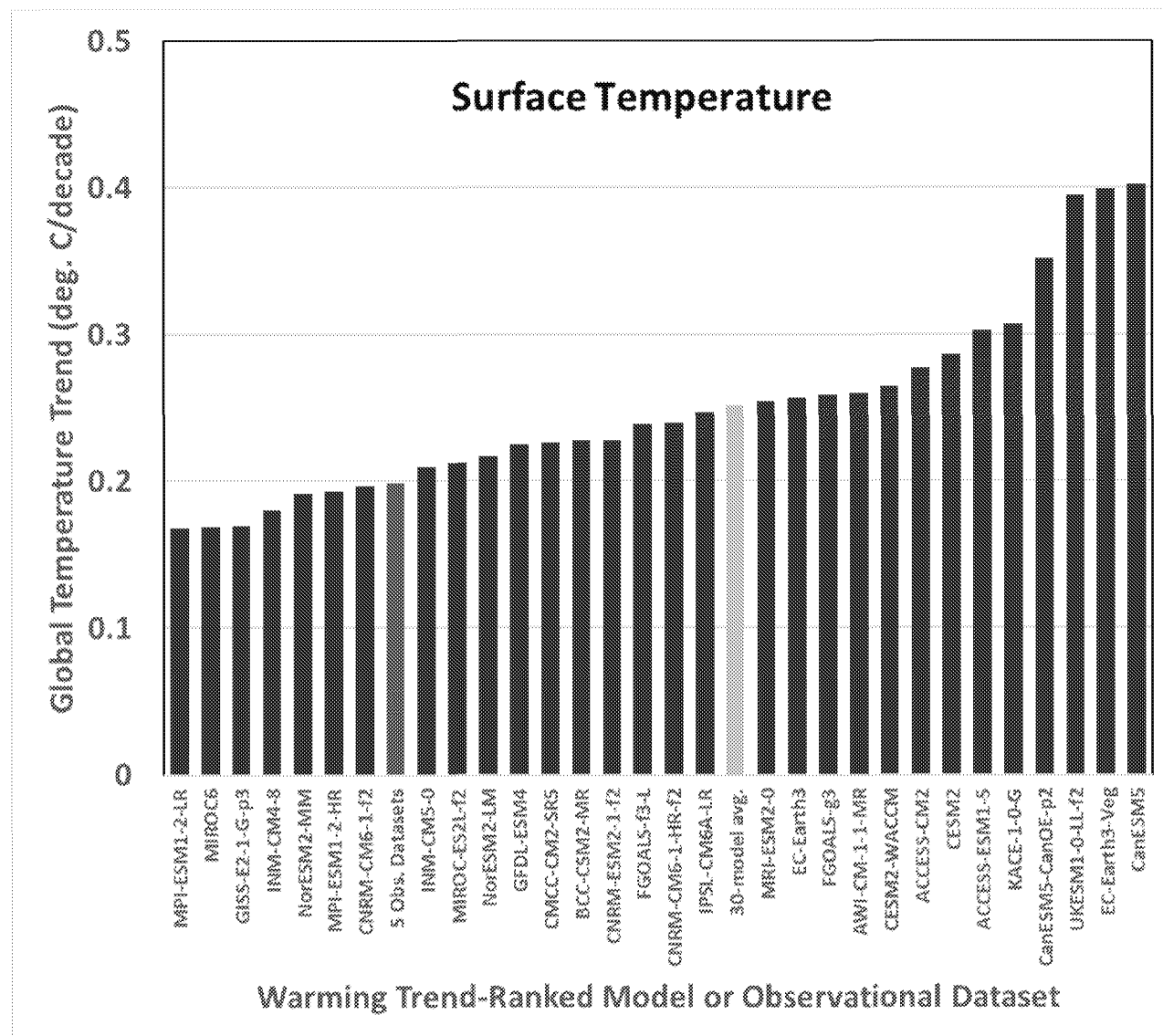


Fig. 5.3 Global surface air temperature trends, 1979-2024, from various CMIP6 climate models (red, 30-model average in orange); and the average of three thermometer datasets (HadCRUT5, NOAA Global Temp, and Berkeley 1 deg.) and two reanalysis datasets (ERA5 and NCEP/NCAR R1) in blue.

From: Steven Koonin <steven.koonin@gmail.com>
Sent: Thursday, May 22, 2025 7:00 AM
To: 'Roy Spencer' <roywspencer@hotmail.com>; 'John Christy' <climateman60@gmail.com>; 'Ross McKittrick'

<ross.mckitrick@gmail.com>; 'Judith Curry' <curry.judith@gmail.com>; 'Travis Fisher' <travis.scott.fisher@gmail.com>
Subject: RE: CORRECTED new Fig. 5.5 (note the 38-model average bar)

Like this figure – it vividly makes the point.

SEK

From: Roy Spencer <roywspencer@hotmail.com>
Sent: Thursday, May 22, 2025 7:05 AM
To: John Christy <climateman60@gmail.com>; Ross McKittrick <ross.mckitrick@gmail.com>; Judith Curry <curry.judith@gmail.com>; Steven Koonin <steven.koonin@gmail.com>; Travis Fisher <travis.scott.fisher@gmail.com>
Subject: CORRECTED new Fig. 5.5 (note the 38-model average bar)

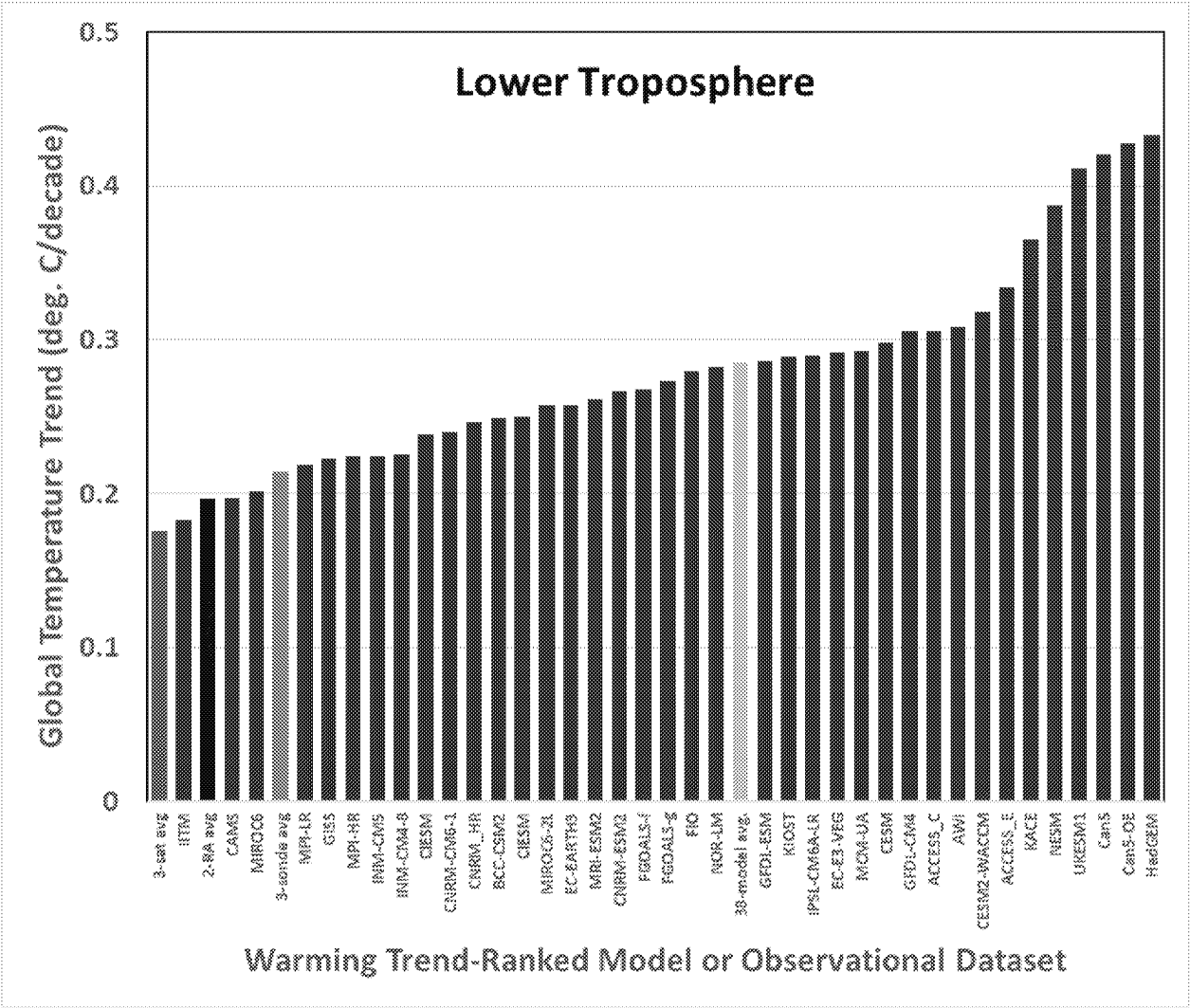


Fig. 5.5 Global lower-tropospheric temperature trends, 1979-2024, from various CMIP6 climate models (red, 38-model average in orange); the average of three satellite datasets (blue); the average of two reanalysis datasets (black); and the average of three radiosonde datasets (green).

From: Ross McKittrick <ross.mckittrick@gmail.com>
Sent: Sunday, April 20, 2025 8:09 PM
To: Travis Fisher; John Christy; Roy W. Spencer; Steven Koonin; Judith Curry
Subject: Apr 20 update

I've created a new dropbox folder called April 20 version which contains the revised outline, the associated chapters and the reference list for all my sections. I took the documents done prior to this point and renumbered the files and sections accordingly.

The new outline is (bold denotes draft posted)

Part I: Human influence on the climate

- 1 Components of anthropogenic radiative forcing and their history to date
- 2 The carbon cycle and future emission scenarios**
- 3 Aerosols and the uncertainties associated with them

Part II: Climate response to anthropogenic influence

- 4 Measuring climate sensitivity to CO2 doubling**
- 5 Models versus observations in recent past**
- 6 Uncertainties in analysis of attribution**
- 7 Evidence on trends and attributable changes in extreme weather**
- 8 Sea level rise

Part III: Impacts on ecosystems and society

- 9 Managing risks of extreme weather**
- 10 Mortality risk from extreme heat and cold
- 11 Climate change and US agriculture**
- 12 Climate change and global greening
- 13 Climate change and economic growth**
- 14 Estimates of the Social Cost of Carbon
- 15 US vehicle-based CO2 emissions and the global climate

Steve: can you draft 1 & 3?

Judy: hoping you can do 8, 10 and 14 (I have info on 14 as well.)

John I think you have something on 15.

Cheers,
Ross

From: Ross McKittrick [ross.mckittrick@gmail.com]
Sent: 4/29/2025 11:20:06 PM
To: Steven Koonin [steven.koonin@gmail.com]; John Christy [climateman60@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]; Judith Curry [curry.judith@gmail.com]
Subject: April 29 update
Attachments: 1 CO2.v.CACs.April29.docx; 0.Front.matter.Apr29.docx; 4.AnthropogenicRF.Apr29.docx

I've created a Dropbox folder called 00.Report Draft where I am hoping we can accumulate current drafts of each chapter (the 00. prefix keeps it at the top of the list).

In the Front Matter file I've put the Table of Contents as best I understand it, with the various additions we've discussed. Also I've put current drafts of chapters 1 and 4, the latter which includes my stab at aerosols. These files are in the Dropbox and attached.

This evening or tomorrow morning I'll populate the folder with the most recent versions of all the other chapters i have. Feel free to do likewise.

1 Carbon dioxide as distinct from criteria air contaminants

This report is chiefly concerned with carbon dioxide (CO₂) emissions from fossil fuel use. Although it has become common to refer to CO₂ as “pollution” this is a misnomer. In the framework of United States clean air policy there are six types of so-called Criteria Air Contaminants (EPA, undated): particulate matter, ground-level ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and carbon monoxide (CO). Air contaminants are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility problems), damage to plants and, at high enough exposure levels, toxicological effects in humans.

CO₂ has not historically been viewed as an air pollutant in the US or elsewhere because it is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation, as will be discussed in this report.

Ambient outdoor air contains about 420 parts per million (ppm) CO₂. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ may be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen et al. (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm.

The main concern about CO₂ is its potential effects on the global climate. This is a very complex question which will occupy much of this report. We will begin in the next section by looking at the role of CO₂ in promoting global greening and agricultural productivity growth, then we will examine the effect of CO₂ on ocean alkalinity. We then turn to CO₂'s role as a so-called greenhouse gas (GHG), beginning with a brief description of radiative forcing, the carbon cycle and the role of aerosols. Part II of this report discusses in detail the topic of the climatic response to GHGs. Part III discusses some aspects of the impacts of climate change on ecosystems and society.

US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. *Environmental Health Perspectives* 124(6) pp. 805-812 <https://doi.org/10.1289/ehp.1510037>

Report of the Special Advisory Group on Carbon Dioxide and Climate Change

Submitted to the Secretary, US Department of Energy

May 30, 2025

John Christy, Ph.D.
Judith Curry, Ph.D.
Steven Koonin, Ph.D.
Ross McKittrick, Ph.D.
Roy Spencer, Ph.D.

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 - 4.1 Components of anthropogenic radiative forcing and their history to date
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 - 4.3 Aerosols and the uncertainties associated with them

Part II: Climate response to greenhouse gas emissions

- 5 Measuring climate sensitivity to CO₂ doubling
- 6 Models versus observations in recent past
- 7 Uncertainties in analysis of attribution
- 8 Evidence on trends and attributable changes in extreme weather
- 9 Sea level rise

Part III: Impacts on ecosystems and society

- 10 Climate change and US agriculture
- 11 Managing risks of extreme weather
- 12 Mortality risk from extreme heat and cold
- 13 Climate change and the Economy
 - 13.1 The Social Cost of Carbon
 - 13.2 Climate change and economic growth
- 14 US vehicle-based CO₂ emissions and the global climate

References

4 Anthropogenic Radiative Forcing

4.1 Components of anthropogenic radiative forcing and their history to date

4.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing atmospheric composition by increasing the emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to outer space. Averaged over Earth, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Human (and some natural) influences on the climate alter this balance and so cause the climate to change.

Influences on the energy balance are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from the IPCC AR6.

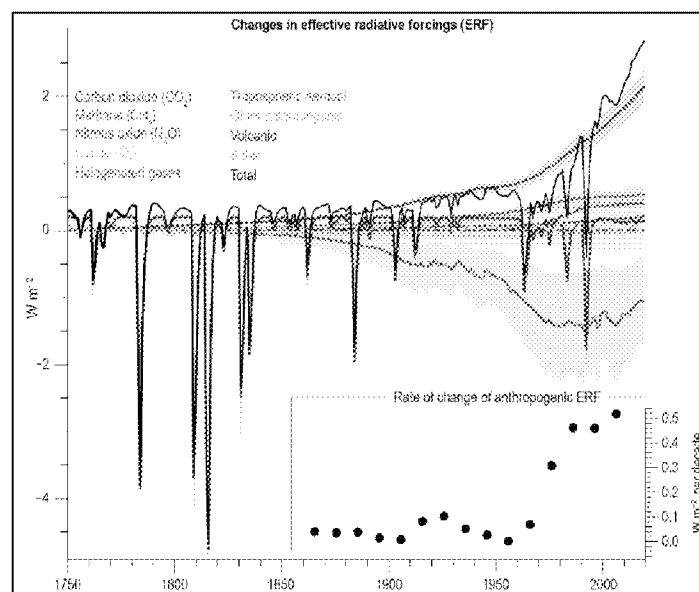


Figure 4.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

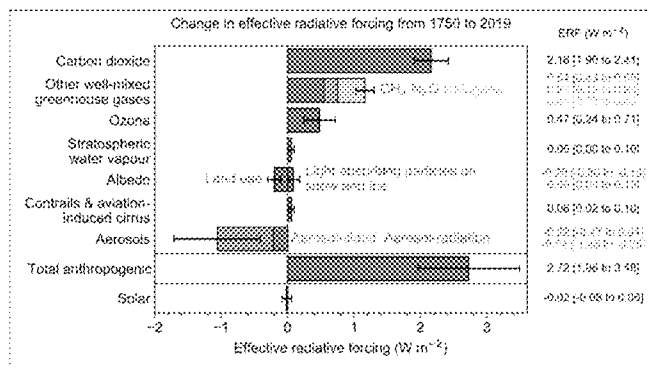


Figure 4.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy-using systems like motor vehicles. Its emissions are accumulating in the atmosphere, as described in the following section. It exerts a warming influence by decreasing the cooling power of the atmosphere. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone), which act similarly, currently add another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding of the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the role of the sun as negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly et al. (2021) review 16 different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval which vary in their implications from almost no change in TSI to a relatively large upward trend. They point out that the variation in TSI reconstructions combined with variations in surface temperature reconstructions implies pairings can be found that are consistent with either no or most 20th century warming being attributable to the sun. A particularly thorny issue is the gap in the TSI data between 1989 and 1991 due to a delay in the launch of a monitor after the Space Shuttle Challenger disaster on January 28 1986, which prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). The question of whether there is an upward trend

in TSI over 1978 to 2018 comes down to how the missing data in that gap are filled. That being the case it is noteworthy that Zacharias (2014) observes the solar research community has been motivated by a desire to downplay any potential role of the sun in climate change so as not to detract from arguments for greenhouse gas abatement:

A conclusive TSI time series is not only desirable from the perspective of the scientific community, but also when considering the rising interest of the public in questions related to climate change issues, thus preventing climate skeptics from taking advantage of these discrepancies within the TSI community by, e.g., putting forth a presumed solar effect as an excuse for inaction on anthropogenic warming.

(Zacharias 2014)

The other natural forcing component is largely volcanic aerosols, which exert an episodic cooling effect.

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing since state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few Watts per sq. meter. Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

4.1.2 Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase.

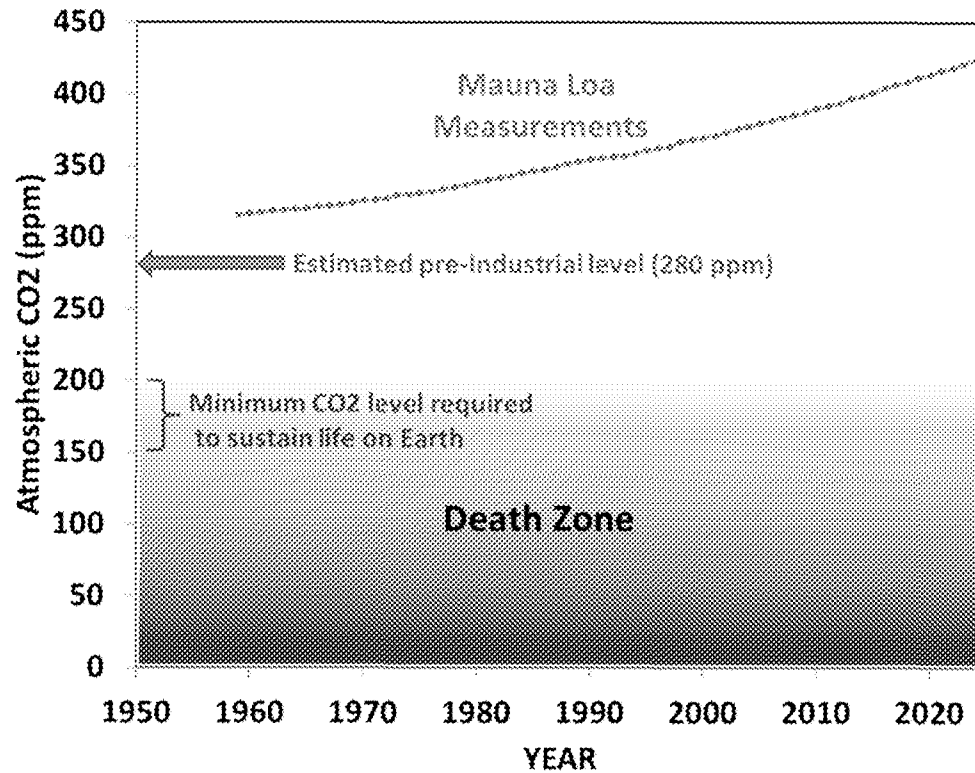


Fig. 4.1.3 Yearly average atmospheric CO2 concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO2 concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). Need source

The annual increase in concentration is only about half of the CO2 emitted because land and ocean processes absorb “excess” CO2 at a rate approximately 50% of human emissions. Thus, future concentrations, and hence future human influences on the climate, depend upon two components: (1) future rates of global human CO2 emissions, and (2) how fast the land and ocean remove extra CO2 from the atmosphere. We discuss each of these in turn.

4.2 The carbon cycle and future emission scenarios

4.2.1 Emission scenarios

Assessing the future dangers of GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future

demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used, and hence were referred to as the SRES scenarios. McKittrick et al. (2012) showed that, when converted to per capita terms, the SRES scenario distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis in Hausfather et al. (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a gain of 2.6 Watts per square meter) projects a GHG concentration pathway which implies warming remains well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

In both the academic literature and popular media RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario. It was used in this way to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading. Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature.

(Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess et al. (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess et al. comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

Widespread use of RCP8.5 has caused a bias towards alarmism in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that between 2010 and 2020 some 16,800 scientific papers had been published using the RCP8.5 scenario, and (p. 16) that about 4,500 of the articles linked RCP8.5 with the concept of “business-as-usual”. They provided analyses of how RCP8.5 was misused not only by individual researchers, but by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They provide the following example (p. 30):

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front-page story, the *New York Times* promoted the report’s misuse of RCP8.5 as a baseline scenario:

“A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United

States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century's end."

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and "business as usual." They conclude (p. 34) that the climate research community has spent a decade "committing scientific resources to science fiction" (emphasis added):

"Derived estimates from RCP8.5 as "business as usual" such as future climate impacts, the impacts avoided from mitigation and the cost effectiveness and benefits of mitigation have no real-world meaning... **The scientific literature has become imbalanced in an apocalyptic direction.**

(Pielke Jr. and Ritchie p. 34)

The IPCC later converted the RCP scenarios to the "Shared Socioeconomic Pathway" or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 was generated using the Resources for the Future Global Energy Outlook tool (RFF 2025). The black line shows total global observed CO₂ emissions from the International Energy Agency (IEA). The solid green line is the emission trajectory developed by BP Energy taking account of current emission control policies and global energy use outlooks. It overlaps a solid black line which represents the emission projection from the IEA also taking account of energy use projections and current policies. The dashed lines show the range of IPCC SSP policies. As of 2023 global CO₂ emissions have been tracking well below the SSP scenarios especially the two highest ones (SSP5-8.5 and SSP3-7.0).

Carbon dioxide emissions (Million metric tons), by Outlooks & Scenarios. Filtered by Region: World; Fuel: All; Outlook: 2023 Shell (Sky 2050).

Source: RFF Global Energy Outlook at www.rff.org/geo

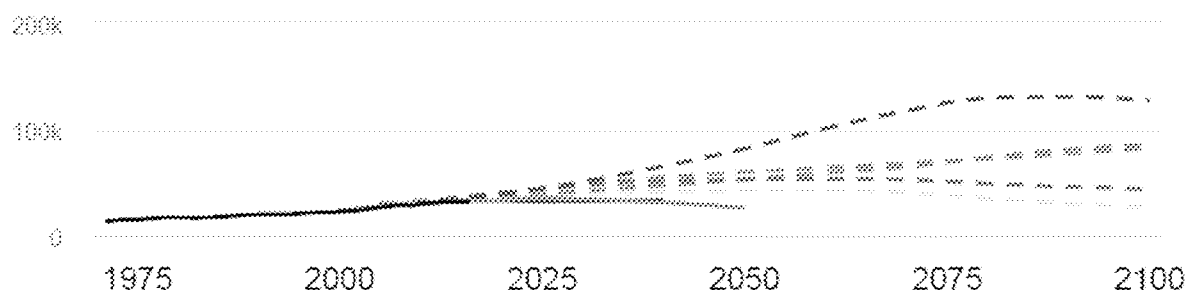


Figure 4.2.1. Observed and projected CO₂ emissions. Source: RFF (2025).

4.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are very large, many times anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-Industrial times, as evidenced by relatively constant levels of atmospheric CO₂ in centuries past derived from air bubbles in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al.

2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue. The scale problem is compounded by recognizing that US motor vehicles account only for about 4 percent of global CO₂ emissions so even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

4.3 Aerosols and the uncertainties associated with them

Climate sensitivity to CO₂ (Equilibrium Climate Sensitivity or ECS) cannot be directly measured in part because it represents the net effect of (at least) two counteracting forces: warming from GHG's and cooling from aerosols. The observed warming can be made to be consistent with a wide range of pairs of these forces. In the following schematic, the warming represented by the red arrow could be due to the High GHG warming/strong aerosol cooling pair, or the Low GHG warming/weak aerosol cooling pair, or something in between.

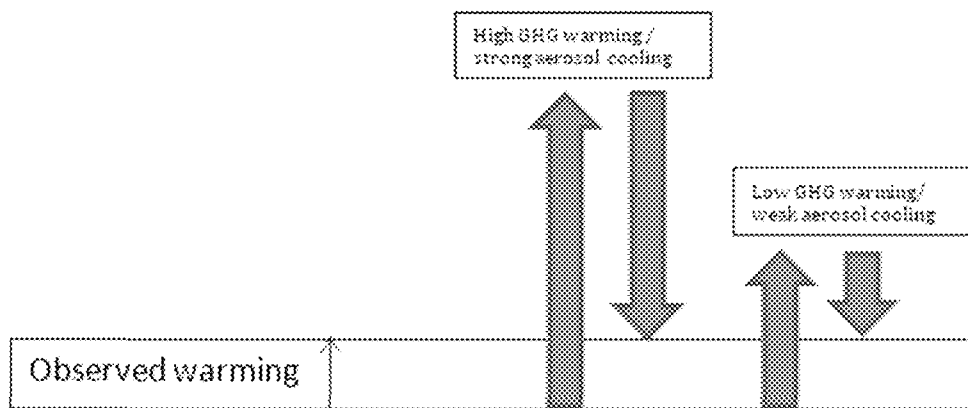


Figure 4.3.1: High and low climate sensitivity to GHGs can be reconciled with the same warming by assuming an offsetting aerosol cooling effect.

Consequently, research on the strength of aerosol cooling is central to forming valid ECS estimates. Lewis and Curry (2018) note that after the IPCC AR5 was published in 2013, eleven studies appeared in the scientific literature all finding that aerosol cooling was weaker than had previously been conjectured. Combining the updated aerosol estimates with greenhouse gas, ocean heat uptake and atmospheric warming data from the IPCC and applying standard empirical methods, Lewis and Curry (2018) estimated the best-guess ECS to be 1.66°C with a 95 percent uncertainty range of 1.15 °C – 2.7°C. They concluded that based on the ECS values derived from most IPCC climate models were incompatible with observed data.

Evidence of lower aerosol cooling (implying lower ECS) has continued to be found, such as Liu et al. (2021). Liu and his coauthors tested the hypothesis that aerosols from wildfires has increased since before the 20th century which, if true, would mean there had to have been relatively strong CO₂ warming over that period offsetting the aerosol cooling. They examined soot layers in ice cores extracted from Antarctica and South America and determined that wildfire activity prior to the 20th century was higher than previously believed. Instead of wildfire activity rising steadily from the 1700s to the present it was high all the way along, which means there was no increase in aerosols over that time—therefore the previously hypothesized aerosol cooling trend in the Southern Hemisphere over the 20th century did not happen. They pointed out how this finding relates to the climate sensitivity issue:

Accurate estimates of aerosol radiative forcing are also crucial for better understanding the transient climate response (TCR) and equilibrium climate sensitivity (ECS) to increasing CO₂ and more accurate projection of future climate change. The negative aerosol radiative forcing can, in part, cancel out the positive forcing of increasing

greenhouse gases and contribute to the uncertainty of total radiative forcing. An overly large aerosol cooling implies that models might overestimate TCR and ECS to reproduce historical temperature response. A recent study using one of the latest-generation CMIP6 climate models (E3SM) suggested that reducing both the magnitudes of negative aerosol radiative forcing and climate sensitivity yields a better agreement with the observed historical record of the surface temperature.

(Liu et al. 2021)

Liu told the UK Daily Mail¹

Climate scientists have known that the most recent generation of climate models have been over-estimating surface temperature sensitivity to greenhouse gasses, but we haven't known why or by how much. This research offers a possible explanation.

More evidence pointing to weak aerosol cooling was reported by Wang et al. (2021). They noted that the strength of aerosol cooling is partly mediated by cloud behavior and differs between the North and South Hemispheres because of the different density of aerosol emissions. This allowed them to construct another test of climate model validity, which came out in favor of low ECS models. In their words:

Since anthropogenic aerosols primarily concentrate in the Northern Hemisphere, strong aerosol-cloud interaction models produce an interhemispheric asymmetric warming. We show that the observed warming asymmetry during the mid to late 20th century is more consistent with low ECS (weak aerosol indirect effect) models.

Wang et al. (2021)

To summarize, measuring the effect of CO₂ warming requires making an assumption about the strength of aerosol cooling. While it is very uncertain a substantial body of recent evidence points to it being relatively weak, which implies CO₂ warming is likewise weak. The literature estimating ECS will be reviewed in Section XX.

¹ Available online at <https://www.dailymail.co.uk/sciencetech/article-9629919/Climate-change-warming-effect-greenhouse-gases-overestimated-ice-core-study-suggests.html>

Summary

- The global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.
- The IPCC has downplayed the potential role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it may have played an important role, and the modern record is uncertain due to an interruption in satellite coverage.
- When anthropogenic emissions estimates along with carbon cycle model estimates of atmospheric CO₂ removal are combined we get estimates of future CO₂ concentrations and hence the radiative forcings required by climate models to estimate future rates of warming.
- IPCC emission scenario envelopes have tended to exceed observed trends.
- The vast majority of academic climate “impacts” studies in recent years are based on the RCP8.5 scenario that is considered implausible, and its usage as a business-as-usual scenario is misleading.
- Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set called SSP carries on with this pattern.
- The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small effects, long in the future.
- Measuring the effect of CO₂ warming requires making an assumption about the strength of aerosol cooling. While it is very uncertain a substantial body of recent evidence points to it being relatively weak, which implies CO₂ warming is likewise weak.

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

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Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

From: Judith Curry <curry.judith@gmail.com>
Sent: Friday, May 9, 2025 12:27 PM
To: Roy Spencer; John Christy; Steve Koonin; Ross McKittrick; Travis Fisher
Subject: attribution chapter
Attachments: 5 Climate SensitivityMay09.docx

Latest version of attribution chapter is attached, Ross and I have hashed through this pretty thoroughly, we look forward to your comments

--



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5 Climate Sensitivity to CO₂ Forcing

5.1 Introduction

The sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly, whereas others such as the deep ocean and ice sheets may take decades or even centuries. A related metric which is helpful for analysis on shorter time scales is the Transient Climate Response (TCR), defined as the amount of warming after 70 years in which atmospheric CO₂ increases by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the *likely* range (66 percent probability); the AR5 stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the *likely* range of ECS to 2.5–4.0°C and the *very likely* range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties about ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

5.2 Model-based methods of computing climate sensitivity to GHGs

The ECS ranges for the IPCC AR4 and AR5 were obtained primarily by examining the behaviour of climate models. For the AR6 the IPCC changed course and turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using climate models to try to determine the Earth's climate sensitivity.

ECS represents an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the

historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the model but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for climate models to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

5.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects

need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”
Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

A recent argument, which the IPCC AR6 emphasized, is that data-driven ECS estimates might understate the future warming response to GHGs based on a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but in some regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific, the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value.

However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the

mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) is of greater utility in providing an observational constraint on climate sensitivity. TCR is the amount of warming that would occur at the time when CO₂ doubles, having increased gradually by 1 percent each year over a period of 70 years. Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. The IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of the TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) is 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can estimate the amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a *very likely* range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.⁴⁸

As will be discussed in Chapter 6, a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also, lower values align with evidence from consistent fingerprinting (Section 8) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.6 Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a

median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

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From: Travis Fisher <travis.scott.fisher@gmail.com>
Sent: Friday, May 16, 2025 11:35 AM
To: Ross McKittrick
Cc: Steven Koonin; Roy W. Spencer; John Christy; Judith Curry
Subject: Ch 3
Attachments: 3 Alkaline Oceans.May11[SEK][RM][TF].docx

I didn't see Chapter 3 in the new "01.Report Draft" folder, so I just added the version that includes my comment bubbles to the folder. I'm also attaching it here for convenience.

Excellent work.

For the rest of the chapters, I'll plan to add comment bubbles directly to the version in the "01.Report Draft" folder.

On Thu, May 15, 2025 at 6:54 PM Ross McKittrick <ross.mckittrick@gmail.com> wrote:
Steve you should write a Figure caption for the chapter explaining that.

On Thu, May 15, 2025 at 6:33 PM Steven Koonin <steven.koonin@gmail.com> wrote:

On Figure 2.2:

I constructed that figure from Figure 3 on pg 192 of this paper: <https://ajsonline.org/article/61570-geocarb-iii-a-revised-model-of-atmospheric-co-2-over-phanerozoic-time>

As you can see from the penultimate paragraph on pg 191 of that paper, “a rough value of 300 ppm” is used to represent the present. So “today” would plot as 1.3 on the graph. In fact, here is the caption from the figure as it appears in “Unsettled”

Figure 3.3 Atmospheric concentration of carbon dioxide

beginning at 550 million years ago. Values determined from the

isotopic ratio in carbonate sediments and fossilized soils are relative to

the average over the past few million years; today's concentration would

be about 1.3 on this scale, down in the lower right-hand corner.⁵

Hope this helps.

SEK

From: Travis Fisher <travis.scott.fisher@gmail.com>

Sent: Thursday, May 15, 2025 5:18 PM

To: Ross McKittrick <ross.mckittrick@gmail.com>

Cc: Roy W. Spencer <roywspencer@hotmail.com>; John Christy <climateman60@gmail.com>; Steven Koonin <steven.koonin@gmail.com>; Judith Curry <curry.judith@gmail.com>

Subject: Ch 2

Hi all,

I had a few questions about Chapter 2 (in bubbles in the attached document). My goal is to read closely and comment on every chapter before you guys have your marathon walk-through call. Excellent job on this--I didn't realize how strong the effect of CO2 was on crop water productivity.

Best,

Travis

3. Increasing CO₂ and the Alkaline Oceans

{Ross May 12 edit notes: added citation for pH figure. Moved paleo paragraph closer to start. It was decided to reword various paragraphs to remove passive tense where possible. Expanded discussion of Clements et al – quite an important article – and updated the citation to the published version. Expanded the concluding paragraph}

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

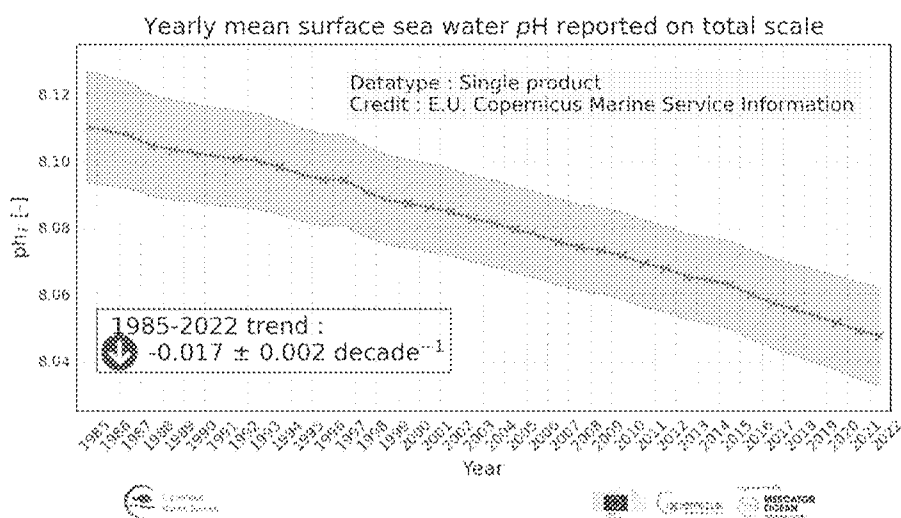


Figure 3.1: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath

et al. (2009) reported that a portion of Australia's Great Barrier Reef (GBR, the world's largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, "As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish." (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a "decline effect": initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the "decline effect" from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.

Clements et al. (2022)

In conclusion, much of the public discussion of the effects of ocean "acidification" on marine biota has been one-sided and exaggerated. Ocean life is complex and much of it evolved when the oceans were acidic relative to the present. There is a tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, whereas the subsequent research rebutting those findings tends to receive little attention.

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From: Judith Curry <curry.judith@gmail.com>
Sent: Wednesday, May 21, 2025 9:31 AM
To: Steve Koonin; Ross McKittrick; John Christy; Roy Spencer; Travis Fisher
Subject: ch 4 revisions
Attachments: 4 Climate SensitivityMay21 Curry.dotx

attached, added text in red

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4 Climate Sensitivity to CO₂ Forcing

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney *et al.* 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5 -- 4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0 - 5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

Climate scientists use multiple lines of evidence to determine the Equilibrium Climate Sensitivity:

- Climate model simulations
- Historical observations

- Paleoclimatic observations
- Process understanding of feedbacks

By itself, the equilibrium warming effect of a doubling of atmospheric CO₂ is slightly more than 1°C.³³ The large values of ECS arise from positive feedbacks that amplify the warming effect of CO₂. Water vapor feedback is positive: a warmer atmosphere may have more water vapor, which itself is a powerful greenhouse gas. Water vapor feedback is partially canceled by the fact that atmospheric temperature decreases more slowly with height above the Earth's surface when atmospheric water vapor increases. Warmer temperatures also result in less snow and sea ice cover, allowing the Earth to absorb more of the sun's radiation. Some simple estimates of these three feedbacks increase the ECS to around 2°C (Sherwood et al., 2020).

Higher values of ECS arise primarily from positive cloud feedbacks. The magnitude, and even the sign, of cloud feedbacks is the greatest source of uncertainty. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for climate models to simulate any of these cloud processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. Historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks,

whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 5.1). Far from settling the model-based sensitivity of climate system uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al, 2020)

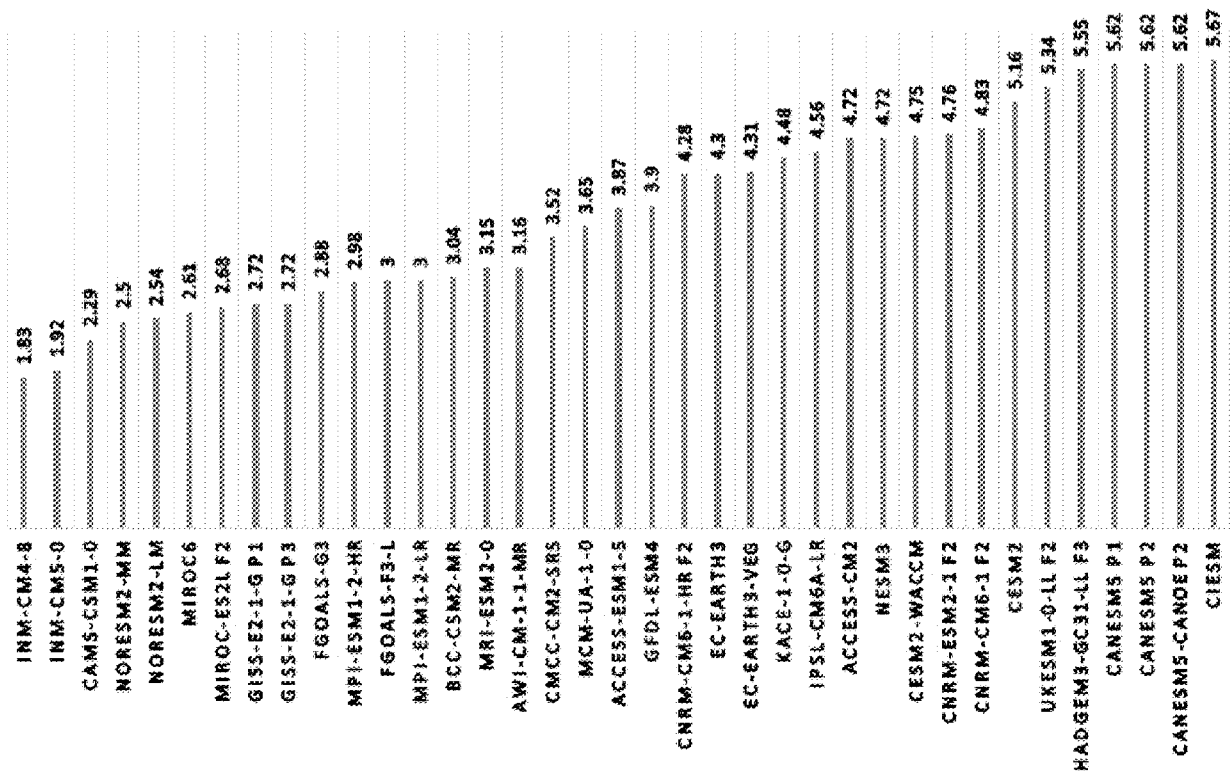


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods, chiefly a recent empirical estimate.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies with the process-based approach and yielded a best estimate of 3.1°C, with a *likely* range of 2.6–3.9°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

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 27. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
 28. Rajendra K. Pachauri and Leo Meyer, *Climate Change*.
 29. Nicholas Lewis, "Objectively Combining Climate Sensitivity Evidence."
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From: Judith Curry [curry.judith@gmail.com]
Sent: 5/8/2025 7:43:52 PM
To: Steven Koonin [steven.koonin@gmail.com]
CC: Ross McKittrick [ross.mckittrick@gmail.com]; John Christy [climateman60@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]
Subject: ch 11 managing risks of extreme weather
Attachments: Dangerous DOE 2.docx

We don't seem to have a chapter for this? I wrote a small blurb for previous (now defunct) chapter, attached. Do we need such a chapter? If so, I could take a crack at this

On Thu, May 8, 2025 at 11:53 AM Steven Koonin <steven.koonin@gmail.com> wrote:

Will do. I also have to finish going through Chapter 6.

SEK

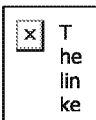
From: Ross McKittrick <ross.mckittrick@gmail.com>
Sent: Thursday, May 8, 2025 2:27 PM
To: Judith Curry <curry.judith@gmail.com>; John Christy <climateman60@gmail.com>; Roy W. Spencer <roywspencer@hotmail.com>; Travis Fisher <travis.scott.fisher@gmail.com>; Steven Koonin <steven.koonin@goolemail.com>
Subject: Ch 7 attribution

Here is a new draft of the attribution chapter. Judy and I did some editing offline for some of the more obscure areas so this version combines our inputs.

I'll post in the Dropbox. Steve maybe you could go through it next.

Ross

--



The
link

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2. Has the U.S. climate become more dangerous over time?

Notions of “dangerous climate change” relate to climate change risk. The IPCC defines climate change risk as the dynamic association of the three core elements of risk: hazard, exposure, and vulnerability. Hazard captures the frequency and intensity of extreme weather and climate events or slowly emerging change such as sea level rise. Exposure refers to the elements of population, infrastructures, and social welfare at risk. Vulnerability refers to the exposures’ potential to suffer as well as its ability to manage, withstand and rebound. Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations.

2.1 Socioeconomic context

The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020. For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population).

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. Over time, population and wealth have increased dramatically in the US, so that when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. A recent estimate finds that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP. <https://drive.google.com/file/d/1MvgwcWaimcn1oHODqNZDG1fXF4M5Idnn/view> By adjusting for inflation, but not for changes in exposure or vulnerability, the NOAA billion dollar data set reflects the growth in population and wealth, which swamps any changes in actual weather hazards. While absolute losses from weather and climate disasters have grown, they are a smaller fraction of GDP today, reflecting economic growth outpacing disaster-related costs.

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exactly numbers are hard to quantify. <https://www.nber.org/papers/w31361> US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation <https://nap.nationalacademies.org/read/12888/chapter/2> Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B <https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew

(1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes. <https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael>. Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers <https://www.tva.com/environment/managing-the-river/flood-management>. During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages. <https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

From: Travis Fisher <travis.scott.fisher@gmail.com>
Sent: Thursday, May 15, 2025 5:18 PM
To: Ross McKittrick
Cc: Roy W. Spencer; John Christy; Steven Koonin; Judith Curry
Subject: Ch 2
Attachments: 2 CO2 and greening.May15.docx

Hi all,

I had a few questions about Chapter 2 (in bubbles in the attached document). My goal is to read closely and comment on every chapter before you guys have your marathon walk-through call. Excellent job on this--I didn't realize how strong the effect of CO2 was on crop water productivity.

Best,
Travis

2 CO₂ fertilization and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1 CO₂ and global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

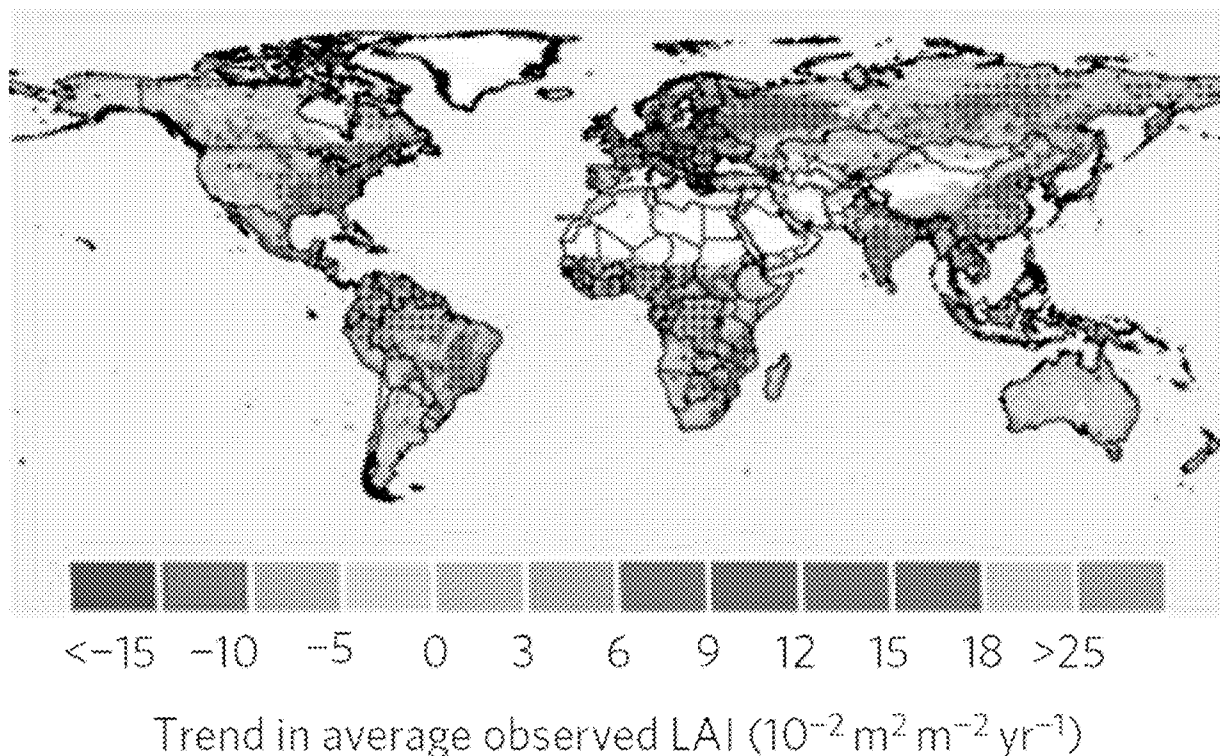


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver.

2.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

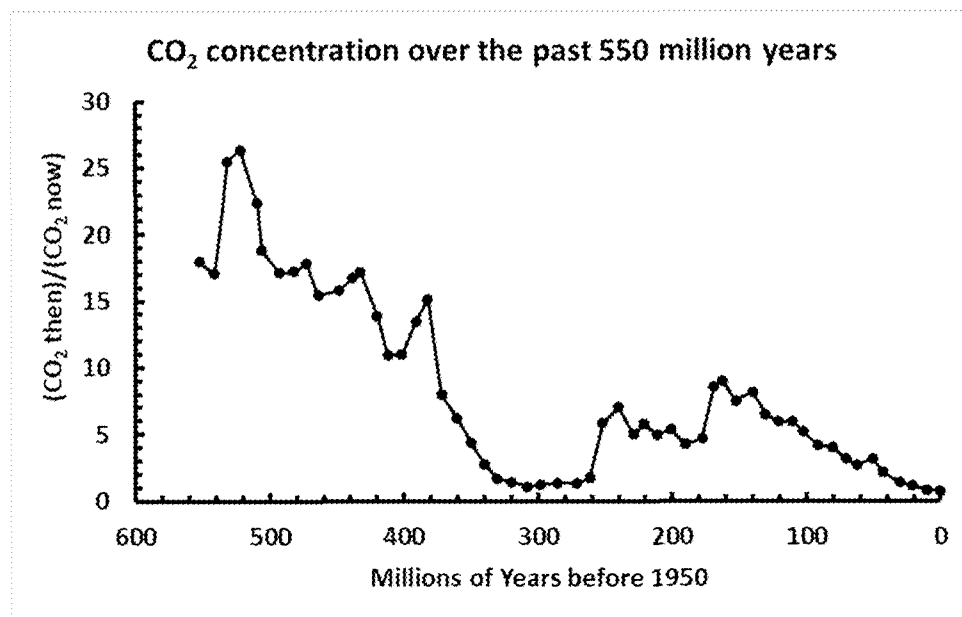


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels.
Source: Berner (2006)

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024).

Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

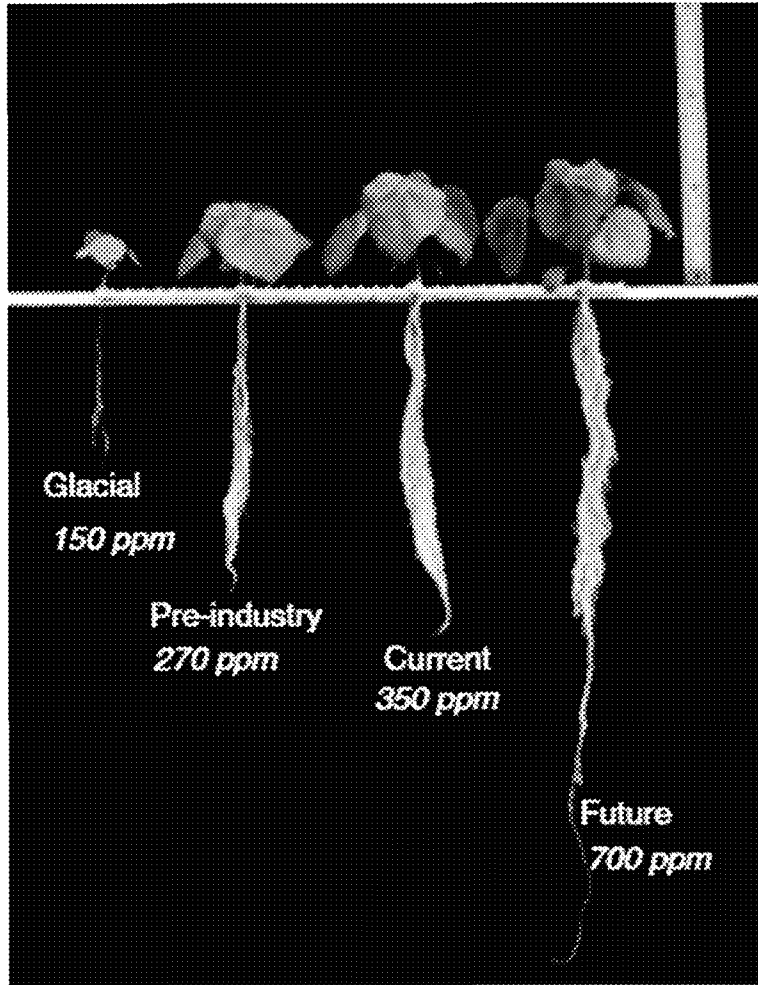


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.3 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

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From: John Christy [climateman60@gmail.com]
Sent: 5/11/2025 7:08:31 AM
To: Ross McKittrick [ross.mckittrick@gmail.com]; Judith Curry [curry.judith@gmail.com]; Steve Koonin [steven.koonin@gmail.com]; Roy Spencer [roywspencer@hotmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]
Subject: Ch 4 Forcing- one point to add.

Section 4.1

The other natural forcing component is largely volcanic aerosols, which exert an episodic cooling influence, though there is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

Jenkins, S., Smith, C., Allen, M. et al. Tonga eruption increases chance of temporary surface temperature anomaly above 1.5 °C. Nat. Clim. Chang. 13, 127–129 (2023). <https://doi.org/10.1038/s41558-022-01568-2>

Schoeberl, M.R., Y. Wang, G. Taha, D.J. Zawada, R. Ueyama and A. Dessler, 2024. Evolution of the climate forcing during the two years after the Hunga Tonga-Hunga Ha’apai eruption. J. Geophys. Res., 129, <https://doi.org/10.1029/2024JD041296>

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Sent: Thursday, May 1, 2025 2:14 PM
To: Judith Curry; Steven Koonin; John Christy; Roy W. Spencer; Travis Fisher
Subject: Ch 5 ECS
Attachments: 5 Climate Sensitivity.May1.Merged.docx

Hi Judy

I posted (& attached) a version of your ECS chapter that cleans up the formatting and merges back in some of the text I had included previously that I think helps it connect to the IAM discussion. I added a couple of comments in red font. I'm reluctant to include a group statement at the end about a likely ECS range. Also I converted the superscripts to insertions where the (name, date) citation will need to be inserted.

Ross

5 Measuring Climate Sensitivity to CO₂ Forcing

5.1 Introduction

The magnitude of the sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly. Others may take decades or even centuries, such as the deep ocean and the cryosphere. A related metric which is sometimes more helpful for analysis on shorter time scales is the Transient Climate Response (TCR) defined as the amount of warming after 70 years in which atmospheric CO₂ goes up by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. With only minor variations this range was adopted and reaffirmed by the IPCC until the most recent AR6. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the *likely* range (66 percent probability); the AR5 stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the *likely* range of ECS to 2.5–4.0°C and the *very likely* range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties about ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise ECS estimate is therefore important for policy guidance.

5.2 Model-based methods of computing climate sensitivity to GHGs

The ECS range has been obtained primarily by examining the behaviour of climate models, but since key components of models are under the control of modelers this is not dispositive of the actual climate's sensitivity. There are approximately three dozen computer climate models operated by research groups around the world (Cannon 2024). GCMs are valuable tools for understanding the climate system from a theoretical perspective. But the models have become so complex, often with 1 million or more lines of computer code (Brown-Steiner 2024), that it would be prohibitively expensive and time consuming for anyone to replicate the models' projections of climate change, let alone test the myriad model approximations embedded in the computer codes; a climate model typically takes hundreds of experts many years to develop (McSweeney and Hausfather 2018). As a result, these models are published in the scientific literature with little to no independent evaluation (Pirtle et al 2010). Climate modeling thus stands as an unusual class of scientific endeavor wherein researchers validating the scientific claims of others — a hallmark of science (National Academy of Science 2019)— becomes impractical, if not impossible.

In large-scale General Circulation Models (GCMs, aka climate models) ECS is not imposed as a direct parameter, instead it emerges from the behaviour of the underlying components of the model. Collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model:

"We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, [emphasis added] as opposed to tuning the aerosol forcing."

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); the rest, to the extent more happens, arises due to climate feedbacks which are inherently more difficult to predict and model. Higher values of ECS arise primarily from positive cloud feedbacks. The magnitude, and even the sign, of cloud feedbacks is the greatest source of uncertainty. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle [source 35]. It is difficult for climate models to simulate any of these cloud processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks [source 36].

ECS can be determined from climate model simulations by doubling the concentration of CO₂, allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, "effective climate sensitivity" is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C [sources 37,38]. Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models.[source 39]

While the models are often touted as being accurate representations of the "basic physics" governing the climate system, they still have problems with model "drift," in which the models slowly change temperature over centuries for no apparent reason (Grandey et al. 2023). The tendency to drift is adjusted for by climate modelers imposing the arbitrary assumption that Earth's climate system does not produce long-term climate change, unless caused by humans (Sen Gupta et al 2013). Suppressing all slow-moving warming and cooling in this way biases model-based research away from potential natural causes of climate change since it implies there can be no warming trends except in response to external forcing. In addition recent research suggests many models do not even conserve energy (Irving 2021) — a violation of the First Law of Thermodynamics. The First Law holds that energy can be neither created nor destroyed; to the extent that climate models fail to conserve energy, it can

spontaneously appear (or disappear) for no apparent reason, causing a fictitious temperature change. This is a particularly important consideration since global warming theory is first and foremost based upon tiny changes in the global energy balance assuming the First Law holds.

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying on other methods in its assessment instead, chiefly a recent empirical estimate.

5.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past. **[source 40]** Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter which appears in the denominator of the resulting equation for ECS. A small amount of uncertainty about the number in the denominator of a fraction can lead to very large uncertainties in the magnitude of the fraction itself. Roe and Baker (2007) pointed out that for this reason uncertainties in climate feedbacks are “highly amplified” in the resulting ECS.

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time the IPCC’s estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth’s temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. **[source 41]** The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data turn out to be smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). An early empirical estimate (Stern and Kaufmann 2000) was 1.6°C, though this predated development of the Energy Balance Model method. Figure 5.1 shows the point or best estimates from 17 subsequent studies all appearing in the peer-reviewed literature since 2012. The Charney range is shown for contrast. The average ECS point estimate in the post-2012 sample is 1.8°C. The highest estimate, from Sherwood et al. (2020), is shown in red: it is the one that was highlighted by the IPCC AR6 and used to guide their assessment of the ECS range (Forster et al. 2021). The one adjacent to it, Lewis (2022), was published subsequent to the AR6 and presented an extensive critique of Sherwood et al. (2020).

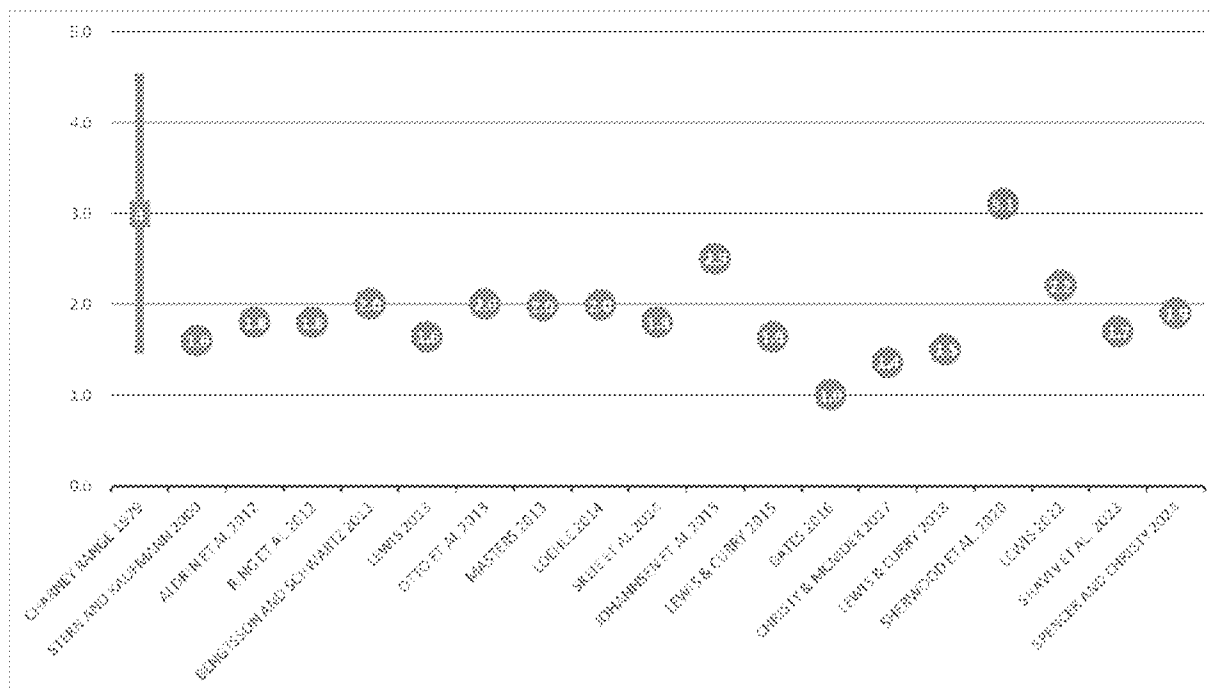


Figure 5.1: Empirical best estimates of ECS. Vertical axis: °C.

[Judy I reinserted this Figure as I think it is an important visual indicator that Lewis 2022 is not a one-off outlier.]

Key concerns raised by Lewis include methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.16°C (1.75–2.7°C in the 17–83 percent likely range), and 1.55–3.2°C in the 5–95 percent very likely range. Lewis' analysis implies that climate sensitivity is considerably more likely to be below 2°C than above 2.5°C. The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis (2022) estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

A recent argument, which the IPCC AR6 emphasized, is that data-driven ECS estimates might understate the future warming response to GHGs based on a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but in some regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value.

However Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic

dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”, in other words GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) is of greater utility in providing an observational constraint on climate sensitivity. TCR is the amount of warming that would occur at the time when CO₂ doubles, having increased gradually by 1 percent each year over a period of 70 years. Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. The IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. **[source 47]** In contrast to ECS, the upper bound of the TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) is 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can calculate the estimated amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a *very likely* range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.⁴⁸

As will be discussed in Chapter 6 a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also it aligns with evidence from consistent fingerprinting (Section 7) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.6 Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a median value of 2.16°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

Estimates of the transient climate response (TCR; TCRE) are more tightly constrained on the upper bound than the ECS.

[Judy I took out the assessed value statement since I don't think we need to generate one and I wouldn't know how to do it]

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems* 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

From: Ross McKittrick [ross.mckittrick@gmail.com]
Sent: 5/8/2025 6:27:17 PM
To: Judith Curry [curry.judith@gmail.com]; John Christy [climatemanager60@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]; Steven Koonin [steven.koonin@googlemail.com]
Subject: Ch 7 attribution
Attachments: 7 Attribution.[RM].May08.docx

Here is a new draft of the attribution chapter. Judy and I did some editing offline for some of the more obscure areas so this version combines our inputs.

I'll post in the Dropbox. Steve maybe you could go through it next.

Ross

7 Uncertainties in Climate Change Attribution

7.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, explain observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement: (Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-

term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

7.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which one dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

7.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all of the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The latter is discussed in Chapter 7. The other two factors are discussed herein. Both of these issues are relevant not only in context of the main policy-relevant statement of the IPCC concerning attribution of the recent warming, but also because the global warming attribution provides the basis for extreme event attribution

7.3.1 Natural climate variability

The IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average, having essentially no net impact on the warming since 1850-1900. This assessment of the contributions of natural variability has been disputed by a number of publications that question the magnitudes of the contributions from solar forcing and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

The IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes for the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). The IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in the AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While the IPCC AR6 shows a substantially greater solar impact than does the AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that you would not infer from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest

significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual

ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

7.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent

fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

7.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to

the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

7.4 Extreme event attribution (EEA)

The IPCC AR6 provides an ambiguous assessment of the role of global warming in the historical record of extreme weather and climate events. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models

to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA's tendency to promote non-peer-reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 8, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series

contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case studies from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

7.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today's climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching

low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

7.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

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From: Judith Curry <curry.judith@gmail.com>
Sent: Wednesday, May 21, 2025 10:18 AM
To: Ross McKittrick; John Christy; Roy Spencer; Travis Fisher; Steve Koonin
Subject: ch 8 earth 20th century warming
Attachments: ch 8 nat var text.docx

New text for the natural variability section is attached

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Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models show too little power relative to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov et al. 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 shows irregular variations of significant amplitude against the background of an overall warming trend. The period between 1905-1945 shows a strong trend of warming. The following thirty years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

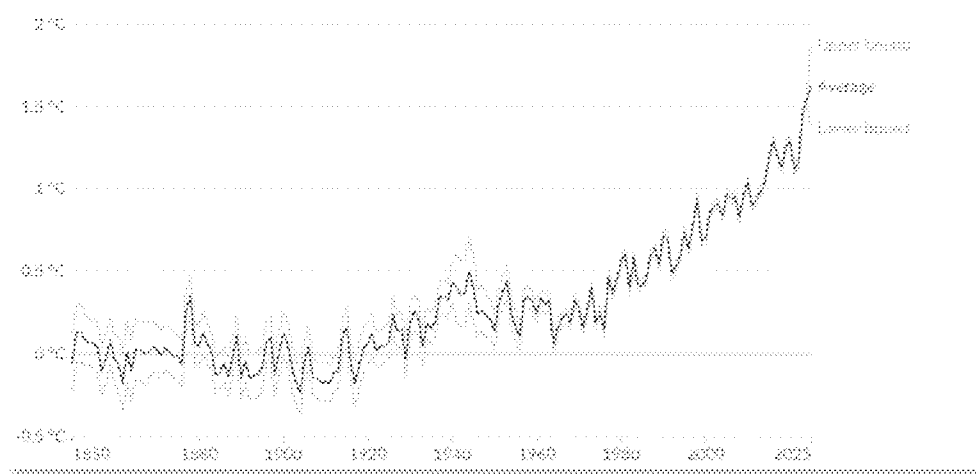


Figure 8.1 Global average surface temperature.

The causes of the early 20th century warming is discussed by Hegerl et al. (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941; hence this implies that the early increase in CO₂ had a small impact on the warming. Volcanic activity during this period was very low, and solar forcing is uncertain. Hegerl et al (2017) somehow inferred that 40-54% of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman et al (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that most likely these variations were caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity as well as growing greenhouse gases concentrations. Tokinaga et al (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale over the Northern Hemisphere. These same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes for the cooling have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation;

cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson et al. (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

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From: Ross McKittrick <ross.mckitrick@gmail.com>
Sent: Sunday, May 11, 2025 11:28 PM
To: Judith Curry; John Christy; Roy W. Spencer; Travis Fisher; Steven Koonin
Subject: Ch 8 Extreme weather - new thread
Attachments: 8 Extreme weather.May11.[RM].docx

Here is a suggested version that might work ...

Taking Judy's reduced collection of excerpts I put each one at the start of its section so that any contextual discussion occurs right away. To make these easier to find I pasted them from Judy's document in gray text. I added in the NCA17 heat wave chart. I also put the IPCC Table 12.12 in with an explanation that it's not strictly speaking trend detection and we did attribution in Ch 7 but it's still helpful context.

The chapter sequence is:

- 8.1 Introduction
- 8.2 IPCC Table 12.12
- 8.3 hurricanes and TCs
- 8.4 Temperature extremes
- 8.5 Extreme precip
- 8.6 Tornadoes
- 8.7 Flooding
- 8.8 Droughts
- 8.9 Wildfires
- 8.10 Summary

I took out the AI-generated summary that was in previously since it seemed overly focused on Table 12.12.

8 Extreme weather in the US and elsewhere

8.1 Introduction

Weather extremes, usually related to temperature and/or precipitation, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent unprecedented extreme event is caused by human influences on the climate. That assumption is wrong in two ways. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 8.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.

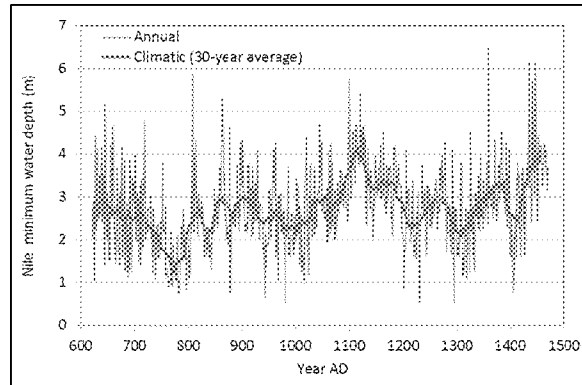


Figure 8.1.1: Nile River discharge [details, source]

With these caveats in mind we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

Note that in the excerpts *italics* are in the original whereas **boldface** emphasis is added.

8.2 Context: IPCC Assessment of signal emergence in extreme weather types

This chapter is concerned with detection of trends. Chapter 7 looked at attribution including for extreme weather. Since there is considerable public interest in the question of whether humans are causing trends in extreme weather to get worse it is useful to begin with the summary Table 8.2.1 which reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). As we discussed in Ch 7 on attribution, AR6 offers conflicting messages about attribution of extreme weather. Nevertheless, we provide this Table for context.

Several patterns stand out. First, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does NOT claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Further, two of the four *medium*

confidence assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

Second, columns 2 and 3 show that the IPCC expects very few anthropogenic trends to emerge within this century, *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, not a “base case” or “business-as-usual” projection. Even so, most weather impacts are not expected to show an anthropogenic signal this century. Natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time.

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8.2.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations

(primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones, or sand and dust storms, and none are expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessments of extreme weather and discussions in the popular media and political arenas.

8.3 Hurricanes and Tropical Cyclones

The AR6 assessed this topic as follows.

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (Chapter 11, p. 1585)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (SPM A.3.4)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (Chapter 11 Summary, p. 1585)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.3.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

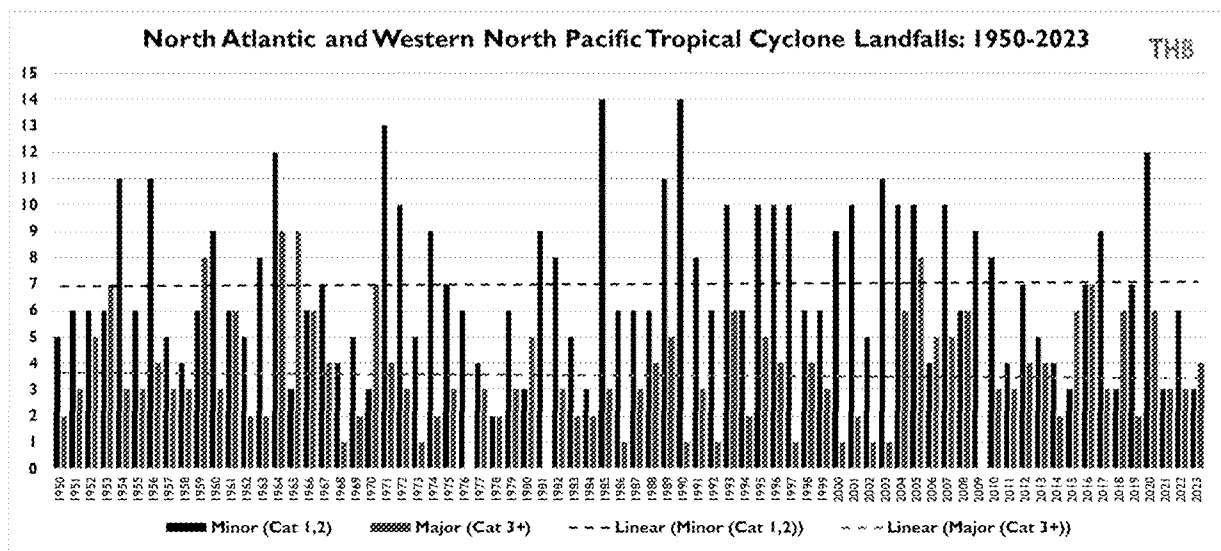


Figure 8.3.1. Tropical Cyclone Landfalls. Source: <https://rogerpielkejr.substack.com/p/global-tropical-cyclones>, Weinkle et al. (2012)

Similarly, Figure 8.3.2 (Maue 2025, <https://climatlas.com/tropical/>) shows that both all hurricanes and major hurricanes have not become more common since 1980, the period of rapidly growing human influences. In fact, both numbers have trended down slightly since the 1990s:

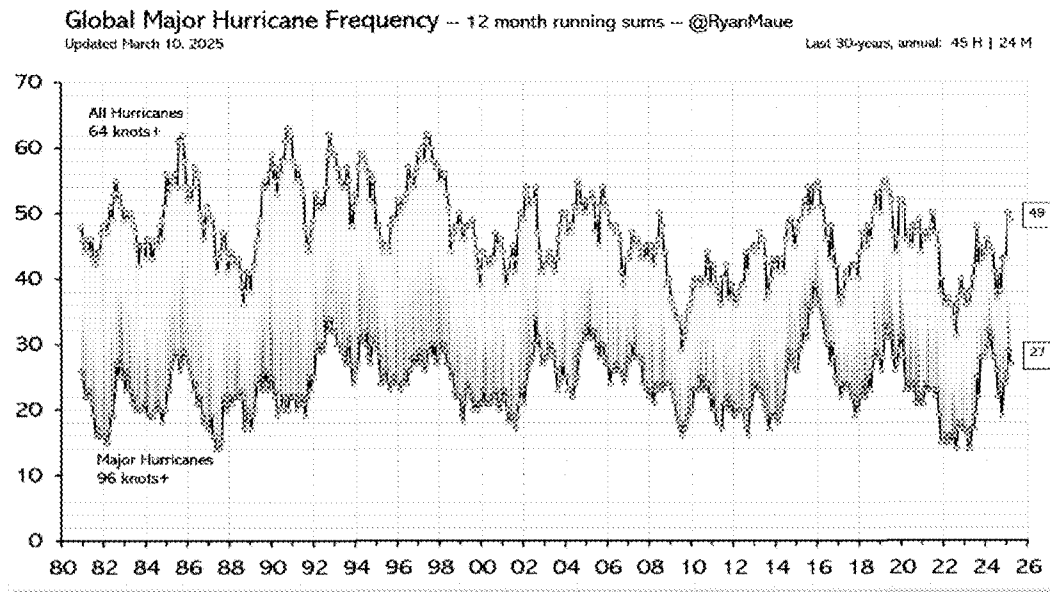


Figure 8.3.2: Global hurricane frequency. Source: Maue (2025)

A metric that combines the number, duration, and strength of TCs is the Accumulated Cyclone Energy (ACE) Index maintained at Colorado State University, shown in Figure 8.3.3. It clearly shows no long-term increase, in fact declining slightly since 1990.

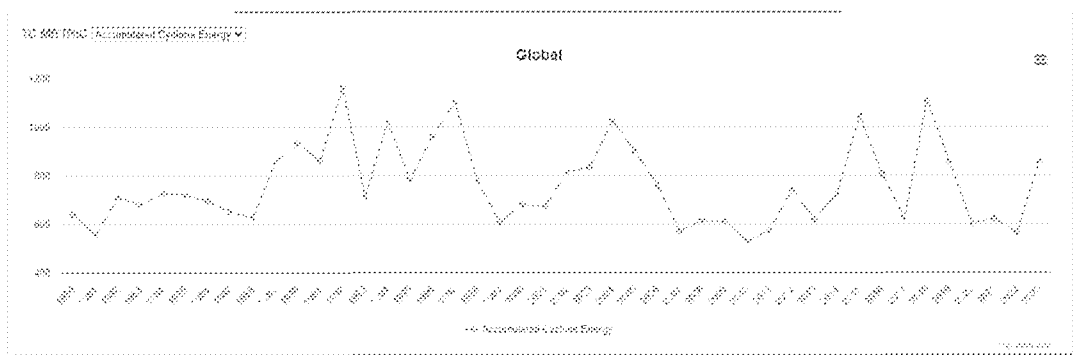


Figure 8.3.3: Global Accumulated Cyclone Energy. Source: Klotzbach (2025) <https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>

Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), another different measure that combines hurricane number, duration, and strength, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

Today's global climate simulations are too coarse to project changes in TCs directly. Rather, projections are derived from finer "downscaled" simulations or proxies involving sea surface temperatures, winds, and aerosols. By those methods, a warming climate is expected to show declining hurricane formation rates. (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020).

8.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: "Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C])." (pp. 190-191)

NCA17: "Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s**." (pp. 190-191)

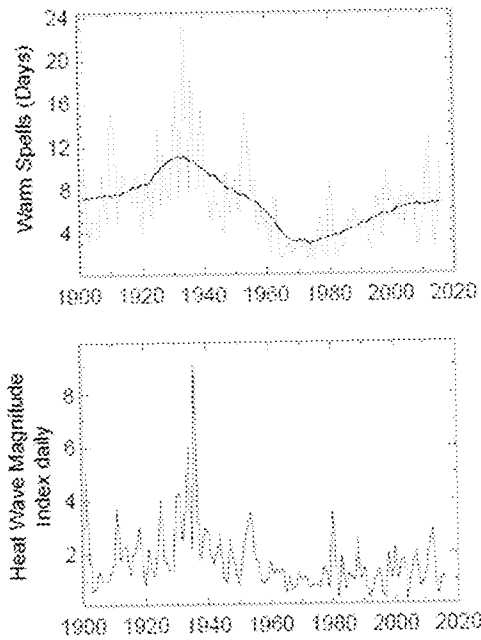


Figure 8.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

8.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 8.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

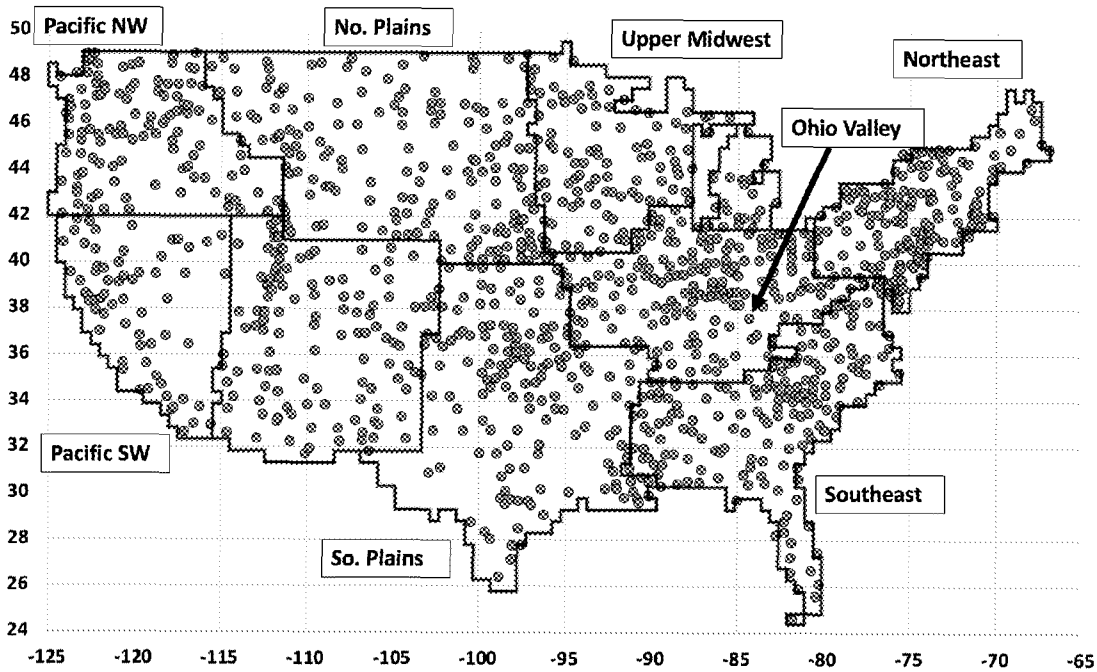


Figure 8.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 8.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

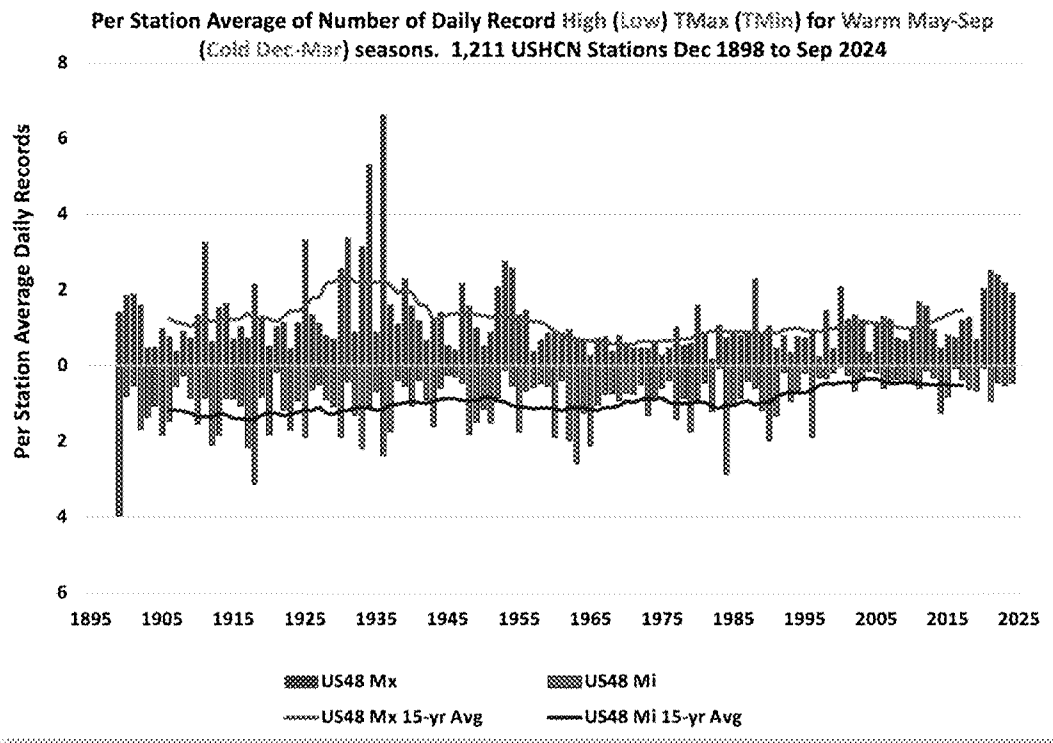


Figure 8.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (IPCC AR5, IPCC AR6, NCA4, NCA5). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.4.4 shows the 15-year trailing average of this measure which has clearly declined over the past century.

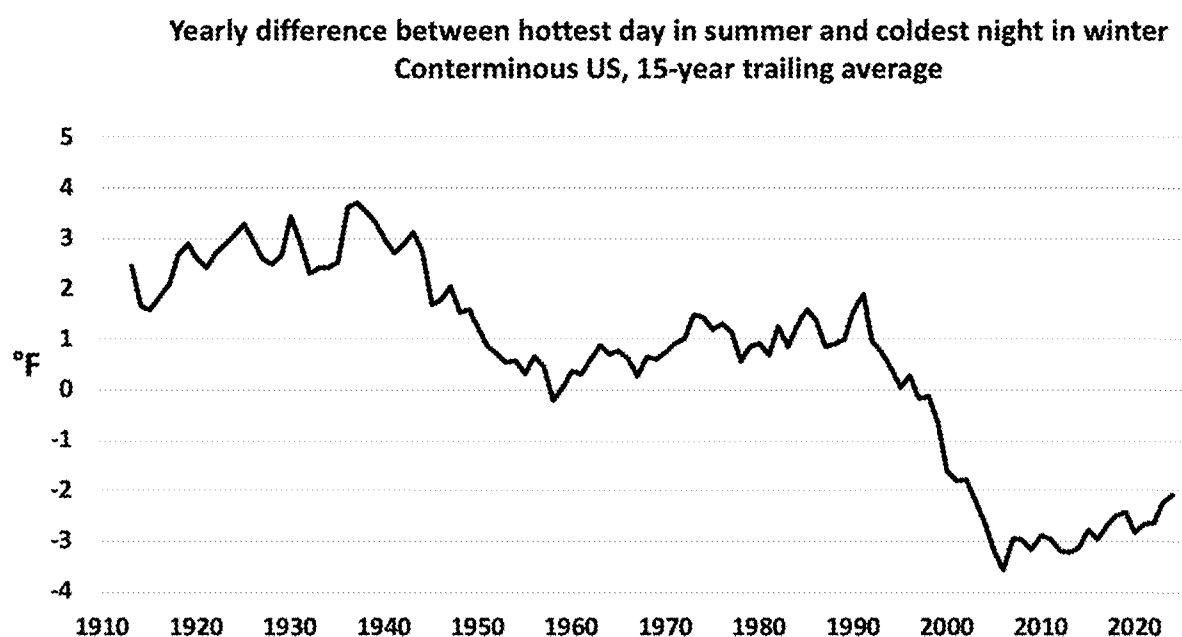


Figure 8.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.4.3 and 8.4.4 while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

8.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

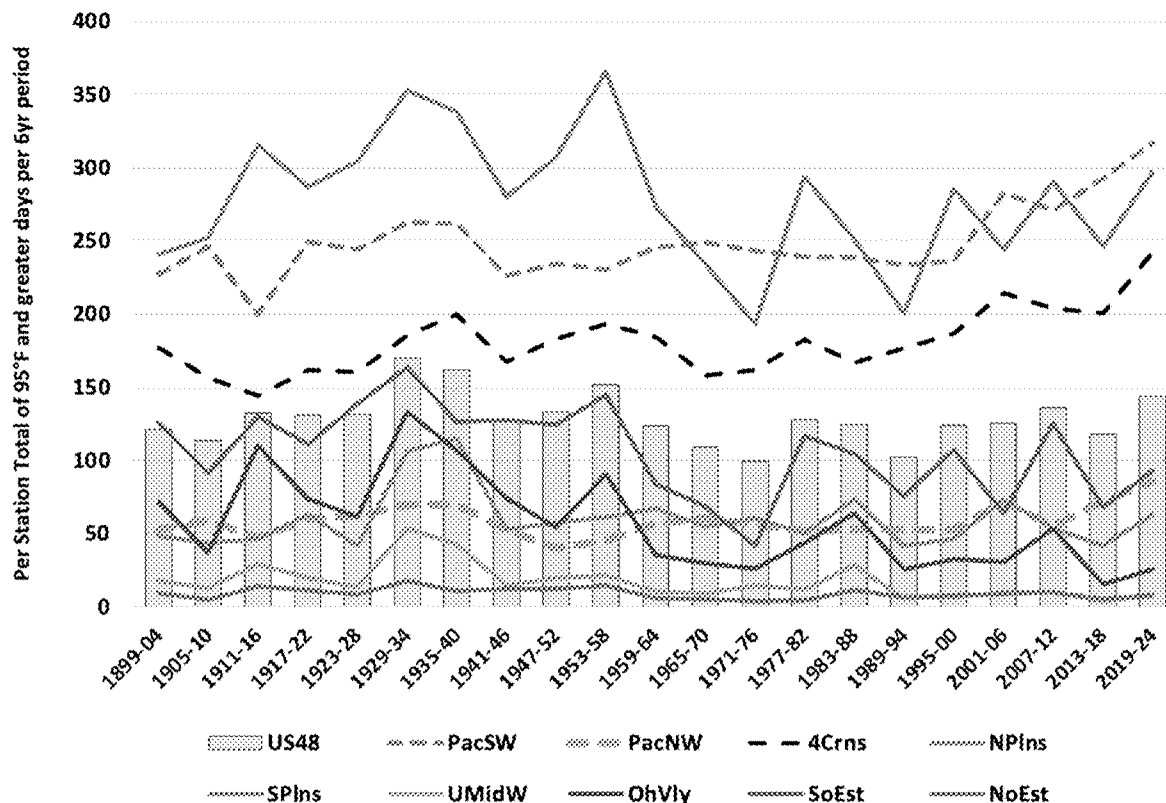


Figure 8.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Source: USHCN, author calculations.

In Fig. 8.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as of the NCA5 claim, an event we examine more closely in Section 6.4. The evidence indicates it was a “black swan” event; *i.e.*, a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme NH grid point summer anomaly in the 46 years from over 4 million grids. In contrast, the global anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

8.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a run of at least six consecutive days. This is equivalent to the method used in NCA5 except that the reference period here is the entire record 1899-2024 while NCA5 truncated the reference period to 1961-1990, a cool time. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

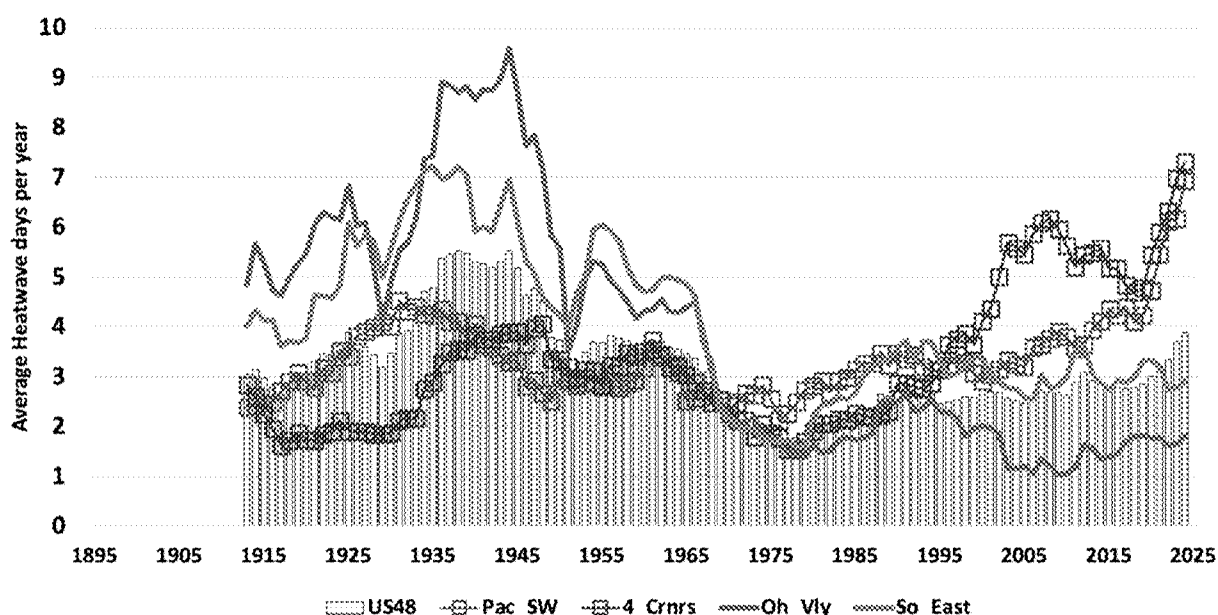


Figure 8.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per

15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

8.4.4 Urban influences

The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

8.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 8.5.1 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

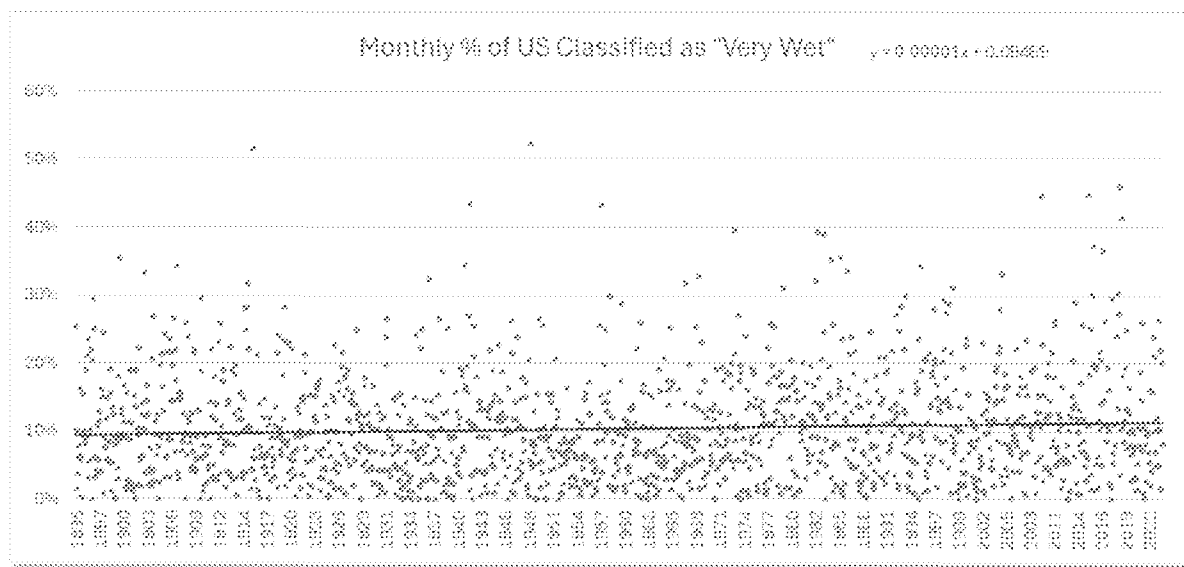


Figure 8.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Because precipitation involves a discrete phase change (water vapor to liquid), it is stochastic and episodic in character and requires careful statistical treatment to understand variability over long time periods (see *8.1 Introduction*). The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a trend counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The results of applying the analysis of McKittrick and Christy (2019) were as follows.

[will generate map of stations -RM]

Pacific region:

- Average precipitation trend is significant (downwards) in Astoria, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport (insignificant elsewhere).
- Averaged over all stations in the region none of these three trend parameters is statistically significant.

Southeast region:

- The trend in average precipitation is positive and significant in Mobile and Quitman, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg and Norfolk, insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Northeast region:

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland, Albany and Buffalo, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland and Gardiner, insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such event in recent history was the ArkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 8.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 8.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences.

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 8.3 shows that the record-setting events then all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 8.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm that struck the region. Evidently such extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 8.5.1 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

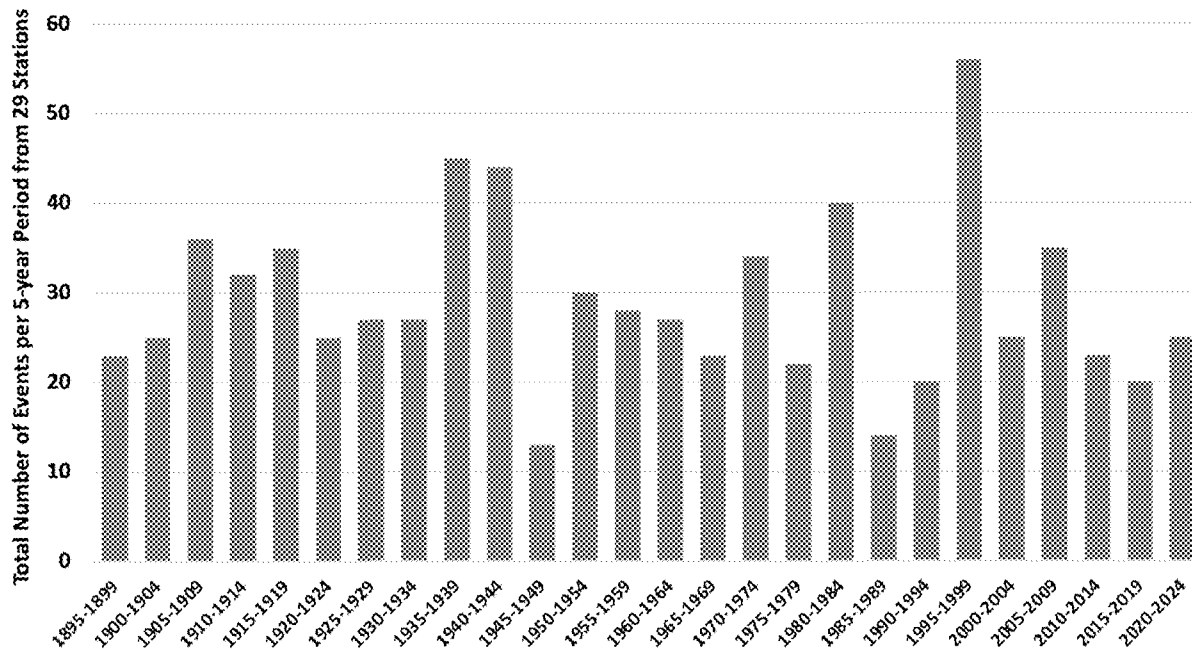


Figure 8.5.2. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event).

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.5.2) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

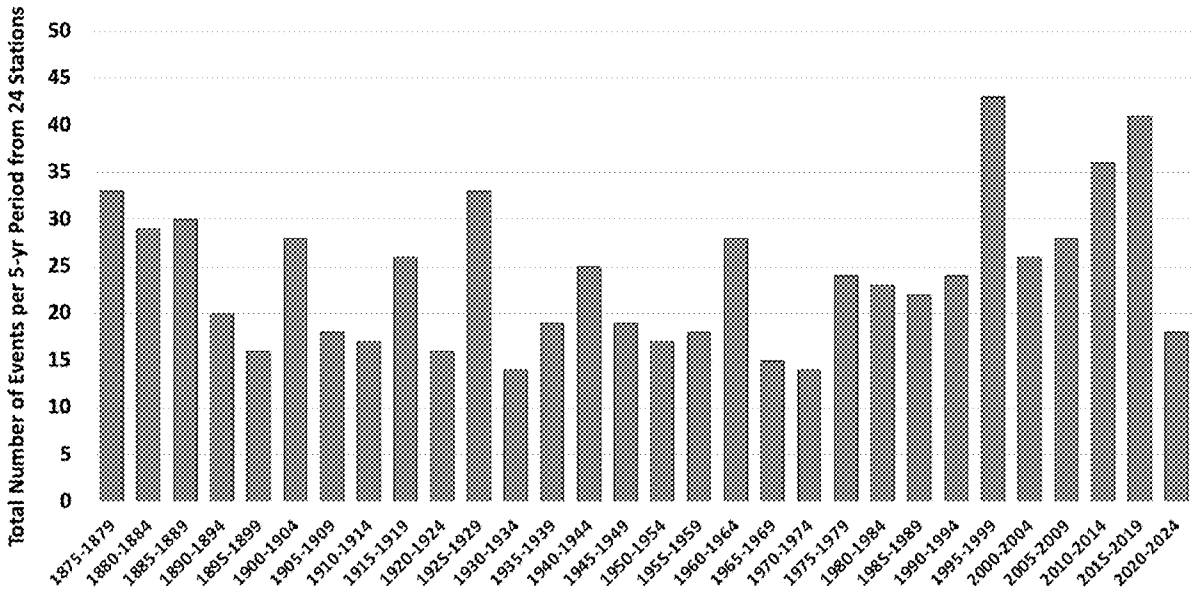


Figure 8.5.3. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

Fig. 8.5.3 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it shall be examined more closely.

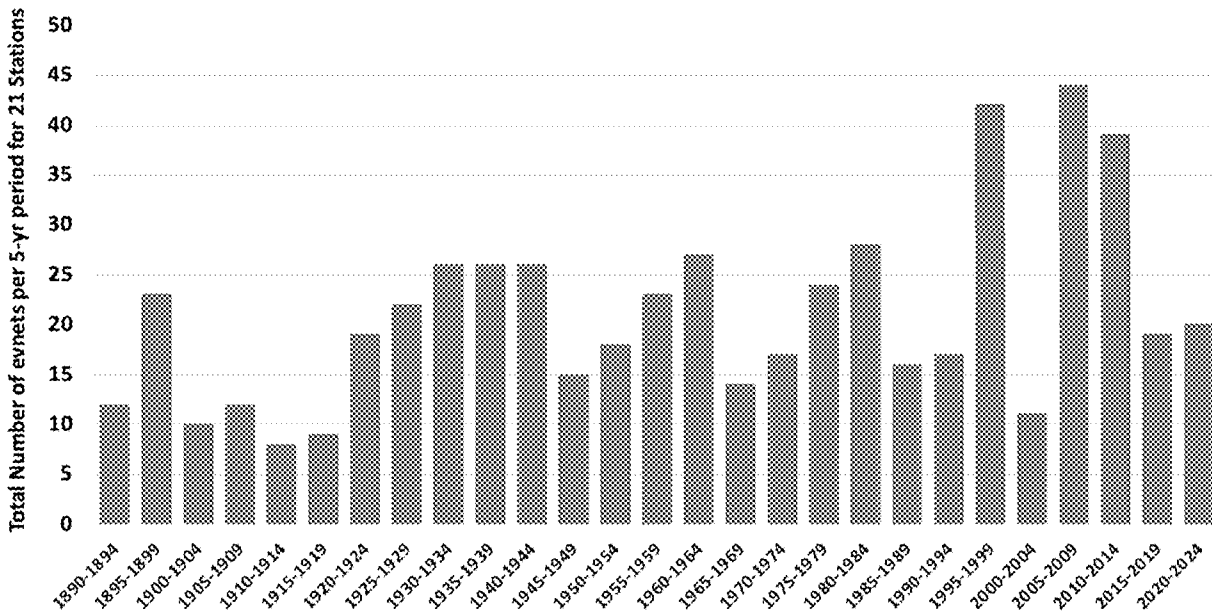


Figure 8.5.4. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. This high percentage increase is due to the very small numbers of the events; only 6 in the first period and 25 in the second. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.5.4 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 0700 LT versus those at Midnight will have differing results for a particular event which would then have major impacts on counting these events. We use the 3-day totals in Fig. 8.5.4 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see Section 8.3.2 above) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Figure 8.5.4 determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In

other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 8.4.7.

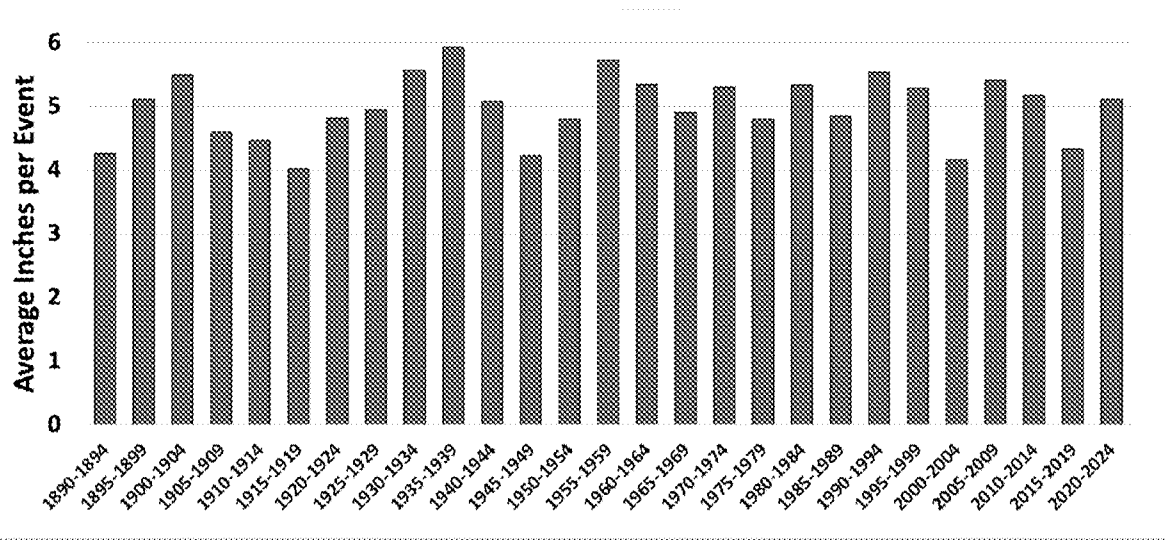


Figure 8.5.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.5.5. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 8.5.4 and 8.5.5 suggest that though there was an uptick in the number of events during the period 1995 to 2014 the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, "Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with

dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 8.17.

In summary, the evidence from the historical record of extreme precipitation events in the CONUS is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes, including a relationship to CO2 concentrations, a result yet to be achieved (McKittrick and Christy 2019).

8.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted there is no evidence of trends in US tornadoes or extreme convective storms.

8.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

8.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 8.8.1 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.001% per year)

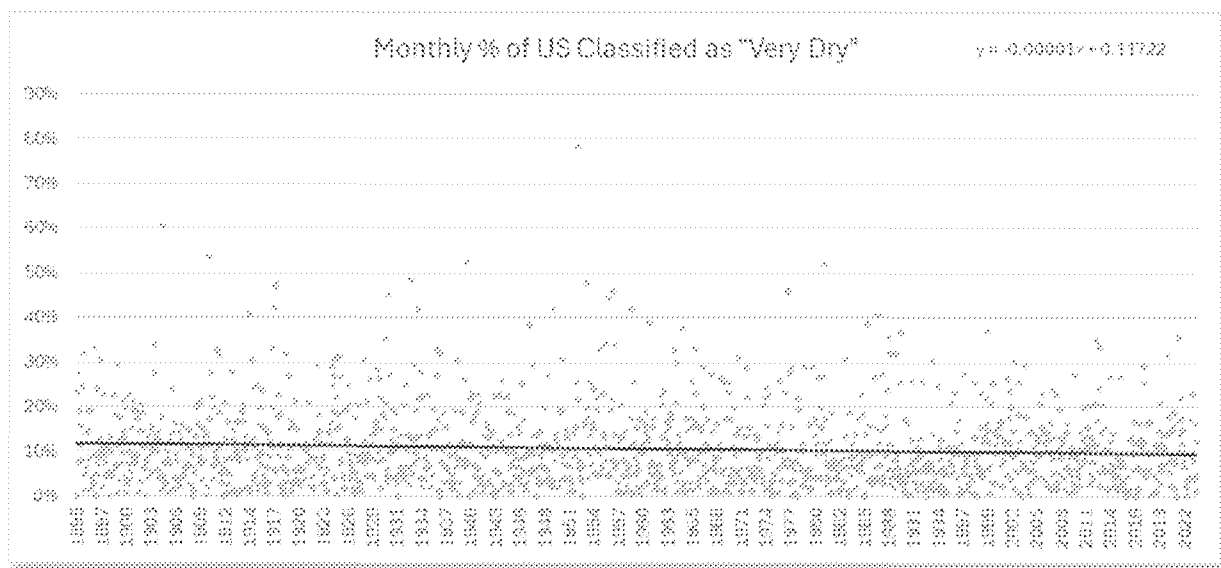


Figure 8.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

8.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 8.9.1 global wildfire activity as measured by European Space Agency shows a downward trend this century.



Figure 8.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

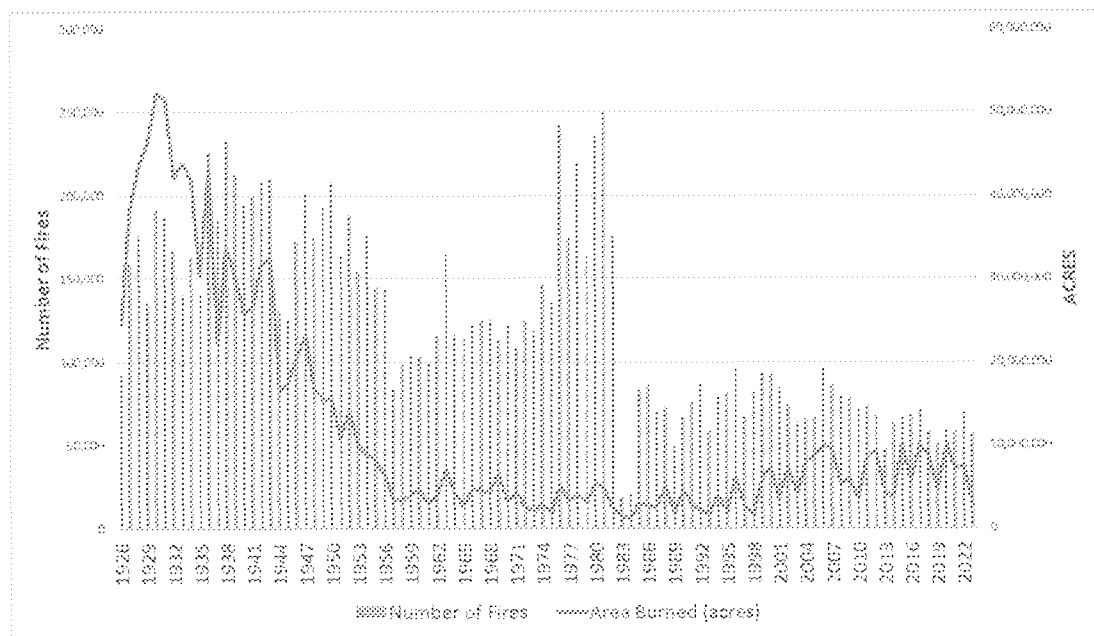


Figure 8.9.2: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived) https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 8.9.3 below (from Figure 2 in their paper).

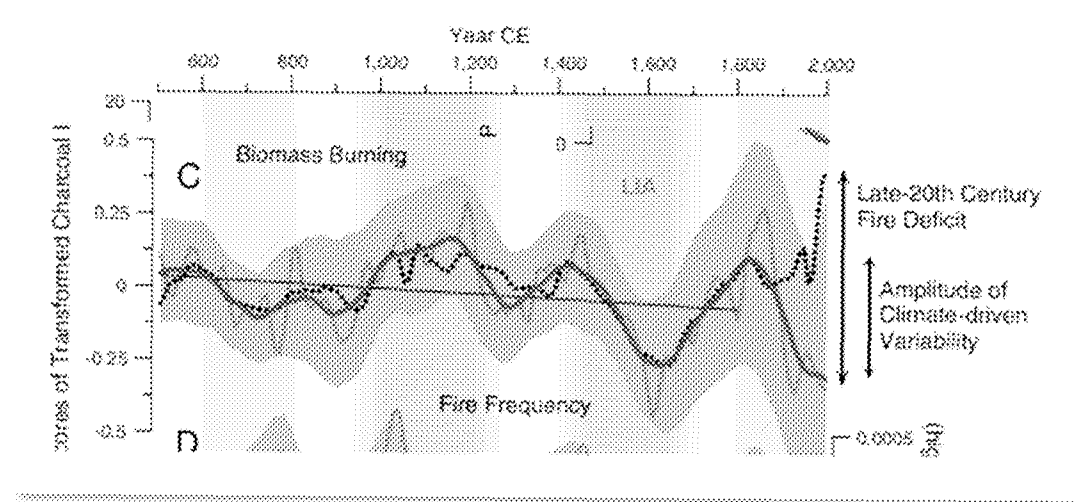


Figure 8.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

8.10 Summary

To be inserted

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From: Ross McKittrick [ross.mckittrick@gmail.com]
Sent: 5/6/2025 2:47:29 AM
To: John Christy [climateman60@gmail.com]; Judith Curry [curry.judith@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]; Steven Koonin [steven.koonin@googlemail.com]
Subject: Ch 8 Extreme weather
Attachments: 8 Extreme weather.RM.May05.docx

I have wrangled the extreme weather chapter into something I hope flows better and is more readable. I adopted Judy's editorial changes and then the new changes I made are in red. I added some new Figures showing results on PC and SE data and will add the NE chart when I get the data. I also made some labeling suggestions including for the 3 rainfall charts that are hard to understand. Section summaries and an overall summary are still needed.

Ross

8 Evidence on trends and attributable changes in extreme weather

8.1 Review of prior expert assessments

It has become routine in popular discussions and media representation of climate change to assert that extreme weather is getting worse globally due to greenhouse gases. Yet expert assessments have not typically concluded this, and instead have emphasized the difficulty of identifying trends or establishing a causal connection with anthropogenic forcing. In this chapter we will start by reviewing the information in previous IPCC and NCA assessments, then we will explore long term patterns in US temperature and precipitation data.

The sources we review will be denoted as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR5: The IPCC *Fifth Assessment Report Working Group 1* (2013).

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8.1.1 Overview: IPCC Assessment of signal emergence in extreme weather types (AR6 WG1 Table 12.12)

Table 8.1 reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). Several patterns stand out.

First, out of the 34 weather impact categories an anthropogenic signal is asserted with *high confidence* in only four, and with *medium confidence* in a further four. For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Second, as shown in columns 2 and 3 the IPCC expects very few such signals to emerge this century *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, it is not a “base case” or business-as-usual projection. Yet even still most weather impacts are not expected to exhibit an anthropogenic signal this century. As will be clear from the underlying report text, natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trends reversals over time.

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
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Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessment of extreme weather and discussions of extreme weather in the popular press. As we show below the Table reflects longstanding conclusions of the IPCC and other assessment bodies. In the next few sections we will simply present without comment excerpts from past assessment reports.

Notes: in these excerpts bold-face emphasis is added. Italicized emphasis on *confidence* terms is in the original sources. Citations contained in quoted text can be found in the underlying reports but are not reproduced here.

8.1.2 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, **there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.**

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shiklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier spring flow in snow-dominated regions (Seneviratne et al., 2012).

In summary, **there continues to be a lack of evidence and thus *low confidence* regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.**

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is *low*, but there are regions experiencing increases**, including parts of Asia, southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

“The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**”

8.1.3 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/ or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, **the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease** (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land

mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4). As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.**

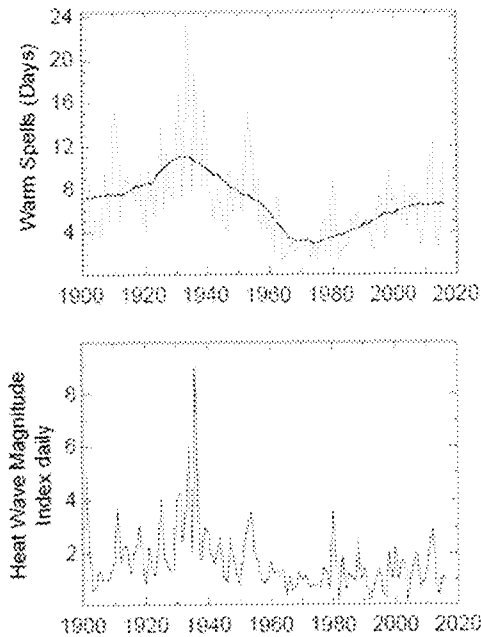


Figure 8.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8.1.4 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is *medium confidence* that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8.1.5 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that **it is likely that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but there are strong regional and subregional variations in the trends**. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing**. One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States**. Formal detection-attribution studies indicate a human

contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

8.1.6 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The SREX assessed that there is *low confidence* in observed trends in tornadoes and hail because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, there is *low confidence* in past trends for hail and severe thunderstorm winds. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

... In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with a decrease in the number of days per year, and an increase in the number of tornadoes on these days (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

... It is extremely difficult to detect differences in time and space of severe convective storms (Kunkel et al., 2013). Although some ingredients that are favourable for severe thunderstorms have increased over the years, others have not; thus, overall, changes in the frequency of environments favourable for severe thunderstorms have not been statistically significant... For hailstorms, such as those that caused disasters in the USA in 2018, detection of the role of climate change in changing hail storms is more difficult, because hail storms are not, in general, directly simulated by convection-permitting models and not adequately represented by the environmental parameters of coarse-resolution GCMs (Mahoney, 2020).

In summary, it is extremely difficult to detect and attribute changes in severe convective storms. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8.1.7 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). **It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust,** after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin.** Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology

used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishatawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.** In addition to trends in TC intensity, there is evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishatawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

Note: The **Underlined** text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. The authors assembled a data set on global TC incidence spanning 1979 to 2017. They claimed that the global fraction of TCs reaching major status (Cat 3—5) rose from 27% in the 1979–1997 interval to 31% in the 1998–2017 interval and the difference was statistically significant. Closer examination of their results however showed a significant increase was only observed in the North Atlantic (18% to 34%) whereas in every other basin (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) the differences were not statistically significant. Kossin et al. issued a Correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>). They now said that the global probability of observing a major TC was 34% in the 1979 to 1997 interval rising to 37% in the later period and the evidence for statistical significance was now weaker, although the authors claimed that the correction did not affect their conclusions.

8.1.8 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation, neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.**

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

p. 233:

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium confidence* (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only

be indirectly related to drought trends; see Box 3-3). However **there is low confidence in the attribution of changes in droughts at the level of individual regions.**

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium confidence* that since the 1950s some regions of the world have experienced more intense and longer droughts. The differences between AR4 and SREX are due primarily to analyses post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than low confidence in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also**

show no long-term trends in soil drying in some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).

There is evidence based on streamflow records of increased hydrological droughts in East Asia (D. Zhang et al., 2018) and southern Africa (Gudmundsson et al., 2019). **In areas of Western and Central Europe and Northern Europe, there is no evidence of changes in the severity of hydrological droughts since 1950** based on flow reconstructions (Caillouet et al., 2017; Barker et al., 2019) and observations (Vicente-Serrano et al., 2019). **In North America, depending on the methods, datasets and study periods, there are differences between studies that suggest an increase (Shukla et al., 2015; Udall and Overpeck, 2017) versus a decrease in hydrological drought frequency (Mo and Lettenmaier, 2018), but in general there is strong spatial variability** (Poshtiri and Pal, 2016). Streamflow observation reference networks of near-natural catchments have also been used to isolate the effect of climate trends on hydrological drought trends in a few regions, but these show limited trends in Northern Europe and Western and Central Europe (Stahl et al., 2010; Bard et al., 2015; Harrigan et al., 2018), North America (Dudley et al., 2020) and most of Australia, with the exception of Eastern and Southern Australia (X.S. Zhang et al., 2016).

p. 1575

Few AR6 regions show observed increases in meteorological drought (Section 11.9), mostly in Africa and South America (NES: *high confidence*; WAF, CAF, ESAF, SAM, SWS, SSA, SAS: *medium confidence*); a few others show a decrease (WSB, ESB, NAU, CAU, NEU, CNA: *medium confidence*). There are stronger signals indicating observed increases in agricultural and ecological drought (Section 11.9), which highlights the role of increased [evapotranspiration], driven by increased [Atmospheric Evaporative Demand], for these trends (Sections 11.6.2.3, 11.6.2.5). Past increases in agricultural and ecological droughts are found on all continents and several regions (WAF, CAF, WSAF, ESAF, WCA, ECA, EAS, SAU, MED, WCE, NES: *medium confidence*), while decreases are found only in one AR6 region (NAU: *medium confidence*). The more limited availability of datasets makes it more difficult to assess historical trends in hydrological drought at regional scale (Section 11.9). Increasing (MED: *high confidence*; WAF, EAS, SAU: *medium confidence*) and decreasing (NEU, SES: *medium confidence*) trends in hydrological droughts have only been observed in a few regions.

AR6 on Attribution (p. 1577)

There are only two AR6 regions in which there is at least *medium confidence* that human-induced climate change has contributed to changes in meteorological droughts (Section 11.9). In South-western South America (SSW), there is *medium confidence* that human-induced climate change has contributed to an increase in meteorological droughts (Boisier et al., 2016; Garreaud et al., 2020), while in Northern Europe (NEU), there is *medium confidence* that it has contributed to a decrease in meteorological droughts (Gudmundsson and Seneviratne, 2016) (Section 11.9). **In other AR6 regions, there is inconclusive evidence in the attribution of long-term trends, but a human contribution to single meteorological events or subregional trends has been identified in some instances... In North America, the human influence on precipitation deficits is complex (Wehner et al., 2017), with low confidence in the attribution of long-term changes in meteorological drought in AR6 regions.**

8.1.9 Summary

- Summary of IPCC and NCA findings To be added

8.2 Other global and continental indicators of extreme weather trends

8.2.1 Tropical Cyclones (TCs)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.2.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

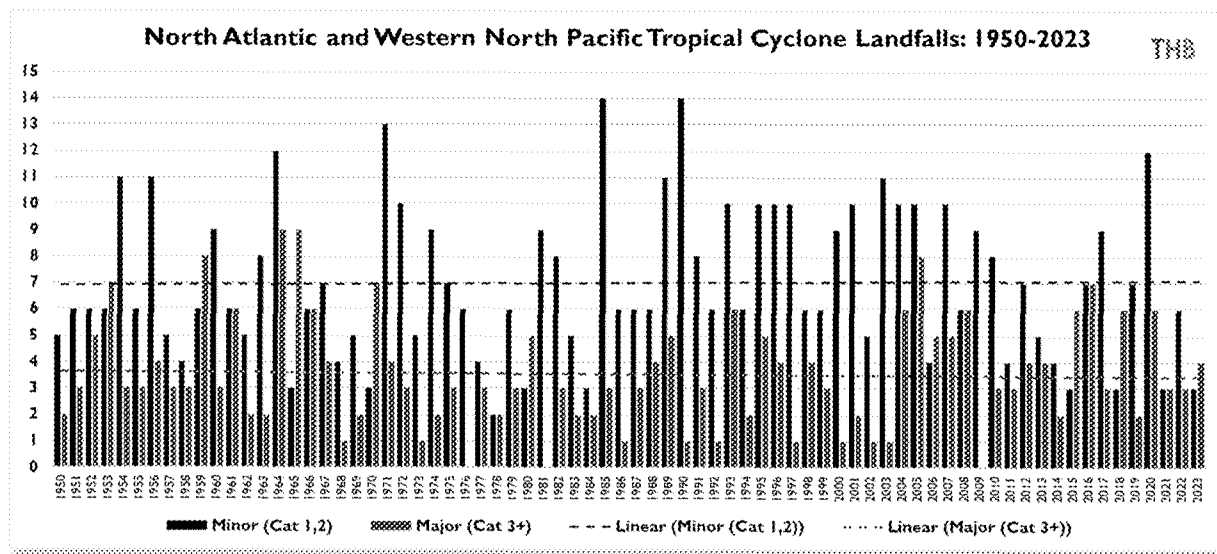


Figure 8.2. Tropical Cyclone Landfalls. Source: <https://rogerpielkejr.substack.com/p/global-tropical-cyclones>, Weinkle et al. (2012)

After 1980, as shown in Figure 8.3, which reproduces data from the Climate Atlas of Dr. Ryan Maue neither the total number of hurricanes nor the frequency of major ones have become more common since 1980, indeed both have trended down since the 1990s:

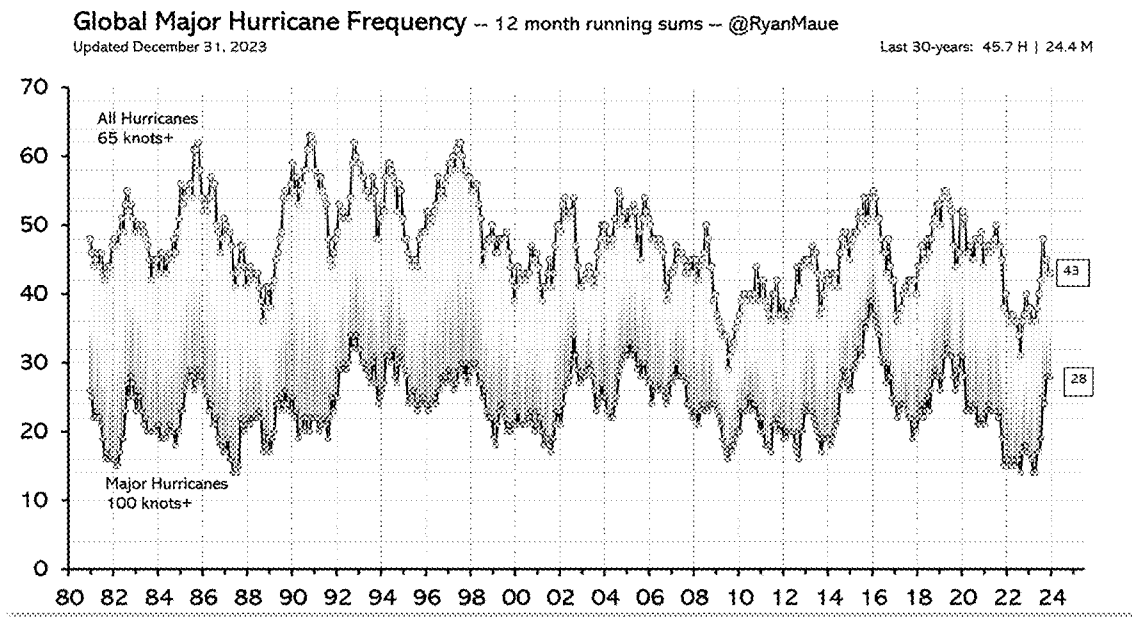


Figure 8.3: Global hurricane frequency. Source: Maue (2024)

A metric that combines the number and frequency of TCs is the Accumulated Cyclone Energy or ACE Index maintained at Colorado State University:

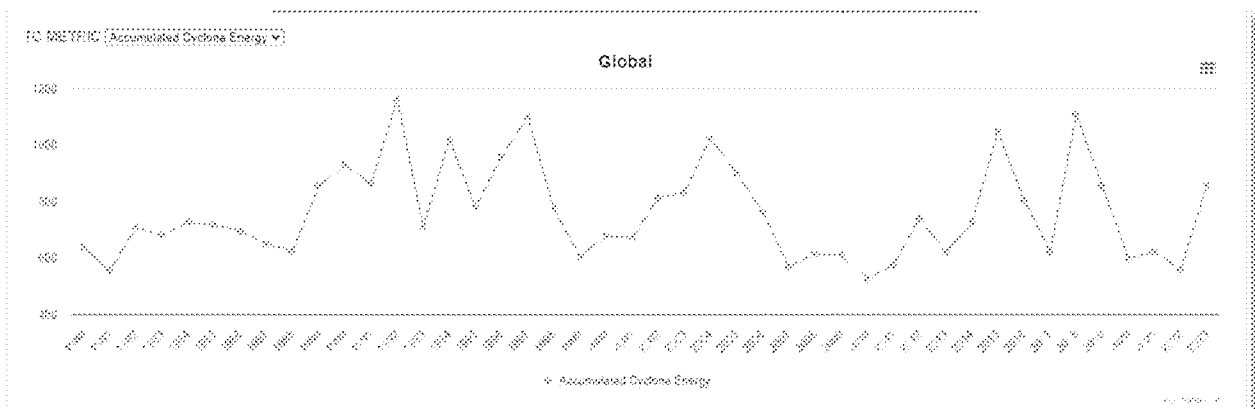


Figure 8.4: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)
<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>

As is clear, it is also not increasing and since 1990 has declined slightly.

Climate models show declining hurricane formation rates in a warming climate (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020). Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), a measure of the destructiveness of hurricanes, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

8.2.2 Wildfires

As shown in Figures 8.6 and 8.7 global wildfire activity as measured by European Space Agency peaked over a decade ago and shows a downward trend since.

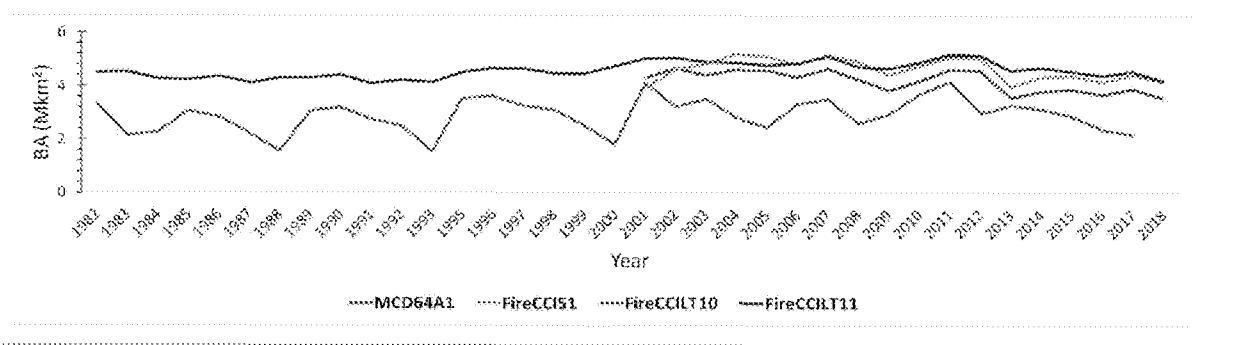


Figure 8.5: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.



Figure 8.6: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

The pattern was summarized by Doerr and Santin (2016):

Wildfire has been an important process affecting the Earth's surface and atmosphere for over 350 million years and human societies have coexisted with fire since their emergence. Yet **many consider wildfire as an accelerating problem, with widely held perceptions both in the media and scientific papers of increasing fire occurrence, severity and resulting losses. However, important exceptions aside, the quantitative evidence available does not support these perceived overall trends. Instead, global area burned appears to have overall declined over past decades, and there is increasing evidence that there is less fire in the global landscape today than centuries ago.**

Regarding fire severity, limited data are available. For the western USA, they indicate little change overall, and also that area burned at high severity has overall declined compared to pre-European settlement. Direct fatalities from fire and economic losses also show no clear trends over the past three decades. Trends in indirect impacts, such as health problems from smoke or disruption to social functioning, remain insufficiently quantified to be examined. Global predictions for increased fire under a warming climate highlight the already urgent need for a more sustainable coexistence with fire. The data evaluation presented here aims to contribute to this by reducing misconceptions and facilitating a more informed understanding of the realities of global fire.

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.7.

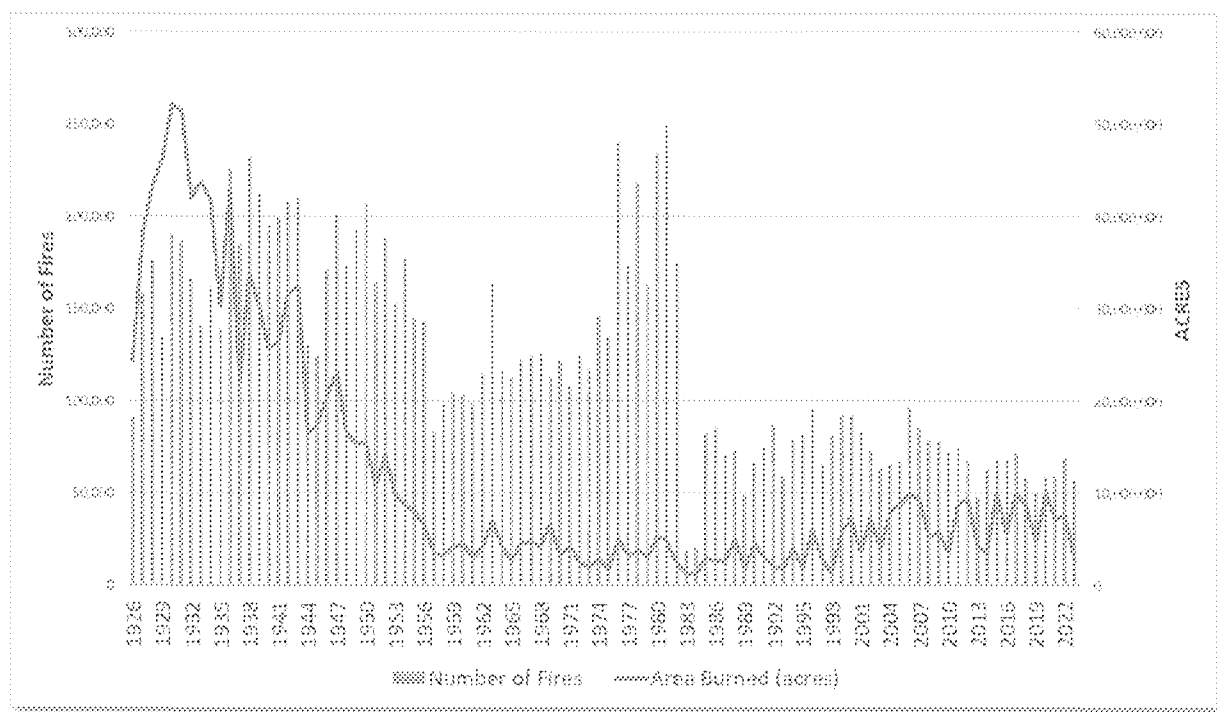


Figure 8.7: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived)

https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other context when measurement systems changed. In this case if anything measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US back 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in the Figure below (from Figure 2 in their paper).

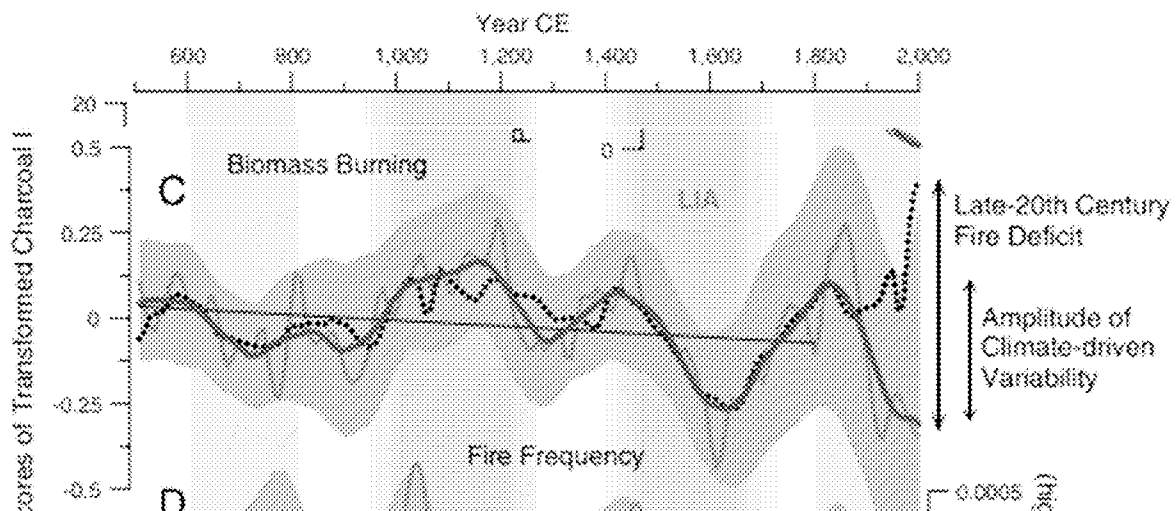


Figure 8.9: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end is the current Fire Deficit, covering the 20th century. In other words, however much fire was observed in the 20th century it was far less than what would have been observed in previous centuries based on the climatic conditions. The authors comment:

The fire deficit identified here might appear to contrast with observations of recent increases in western U.S. fire activity and also to the well established fire-climate interactions documented across the region. These apparent differences can be reconciled by explicit consideration of the time scale of the variations. We show that mean or baseline levels of biomass burned and fire frequency decreased substantially during the past century compared with previous centuries; **the recent increase in “fire activity” (i.e., large-wildfire occurrence) is therefore occurring during a period of unusually low levels of biomass burning.** ... During the past two centuries, however, centennial-scale changes in biomass burned and fire frequency however, are decoupled from climate due to the strong human influences on forests and fires. (p. E541)

Parks et al. (2025) has confirmed that despite the recent increase in wildfire burn area in North America, relative to historical wildfire regimes there remains a significant wildfire deficit.

8.2.3 Precipitation

Figure 8.5 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

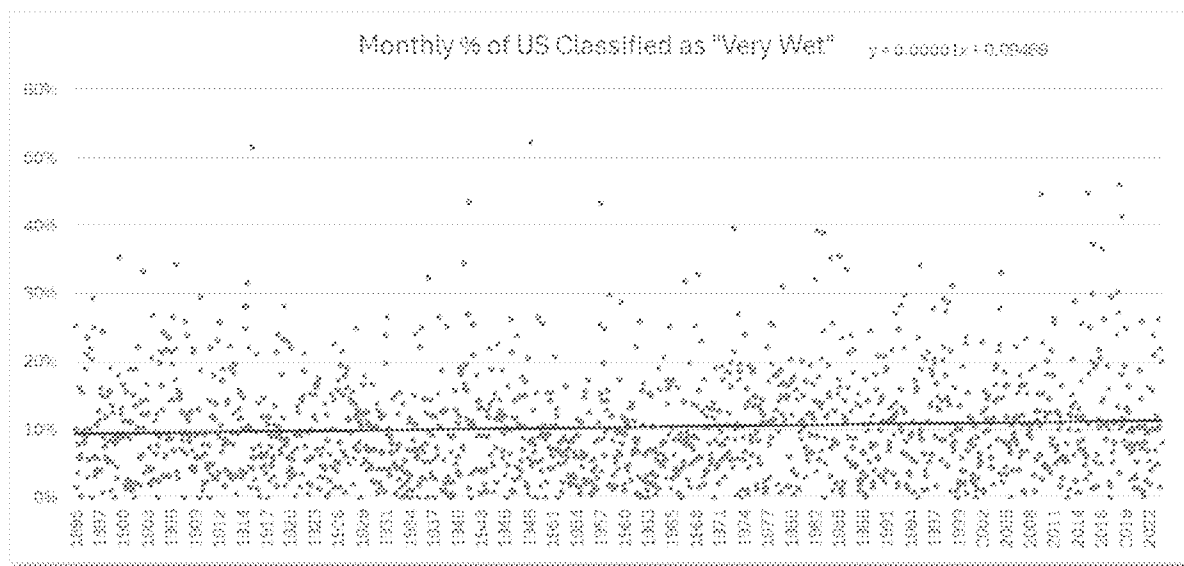


Figure 8.5: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Precipitation will be discussed further in the review of CONUS data below.

8.2.4 Drought

As shown in Figure 8.6 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

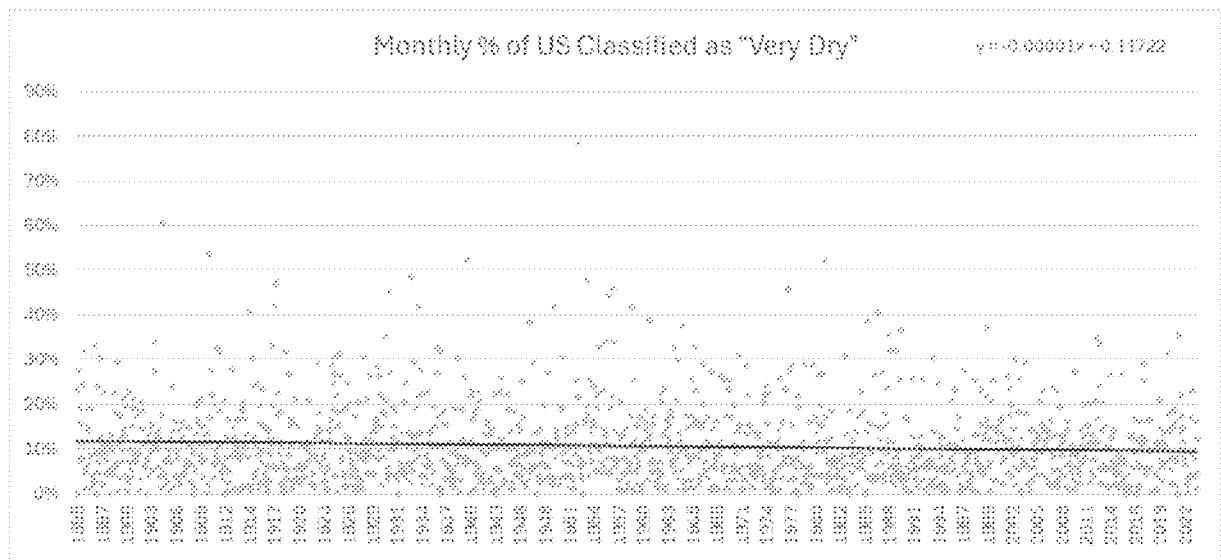


Figure 8.6: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38 year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

8.2.5 Summary

Summary of other indicators to be added.

8.3 Analysis of Conterminous US (CONUS) data on temperature and precipitation extremes

8.3.1 Background: data limitations

Extremes in temperature and precipitation are generally events of short duration that often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these near-surface air temperature or precipitation extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing in response to increases in GHGs (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to undertake quantitative analysis of the variations of extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system is able to generate. Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which humans have never observed, and thus do not enter our databases from which extreme statistics are determined. Thus, assuming that a new climate pattern or event in our lifetime is somehow the result of enhanced GHG concentrations requires the assumption that natural variations are insignificant. This is especially true for precipitation events. With this caveat in mind we examine the evidence for changes in weather and climate extremes.

8.3.2 CONUS daily temperatures are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside in the dataset, with over 1,000 stations any underlying signal we discover-can be characterized by relatively high confidence.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each of these days and each of the stations we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, on average, that a station would experience an average each year of 1.21 the expected number of records for TMax would be 1.21 per year and 0.96 records for TMin 0.96 per year. Figure 8.7 indicates the observed distribution in time of the occurrence of these extreme events.

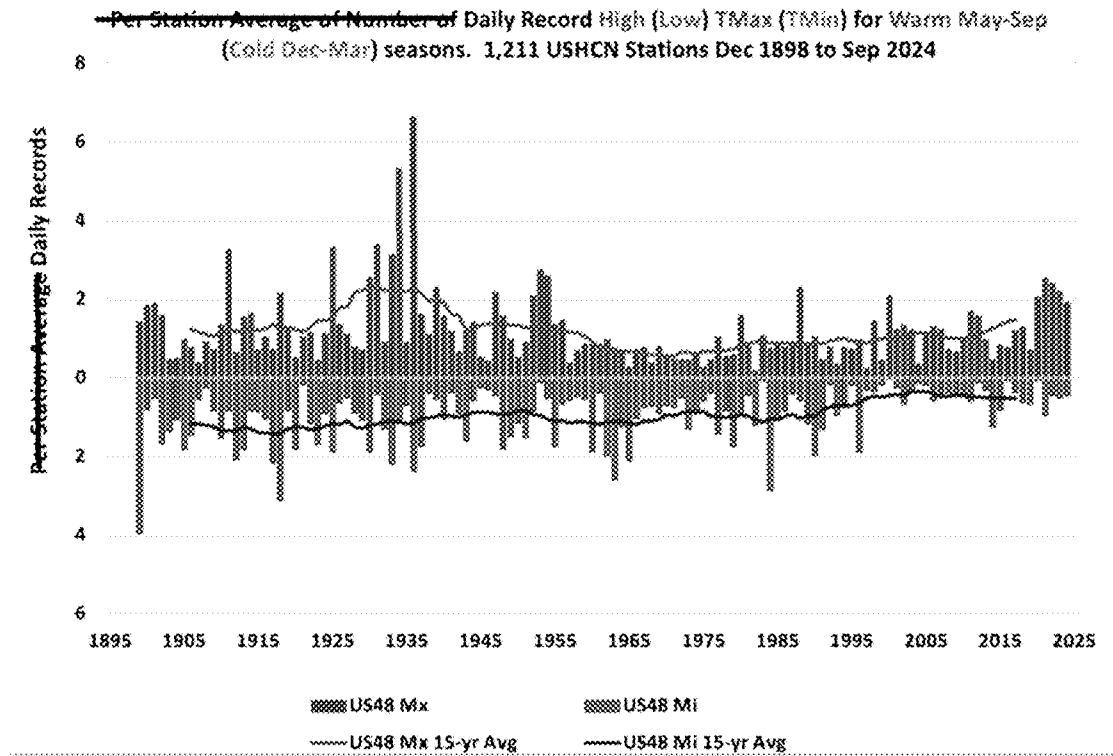


Figure 8.7. I don't think these are per station. I think they are totals across all 1,211 stations every year. E.g. there couldn't be 4 cold records per station in 1899. Per-station-average of Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s. On the cold side other extreme, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. Overall, the number of cold records has declined, especially over the past 25 years. The number of hot extremes has been uneven, reaching a peak in the 1930s. Combining the two records the reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.8. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.8 shows the 15-year trailing average of this measure which has clearly declined over the past century.

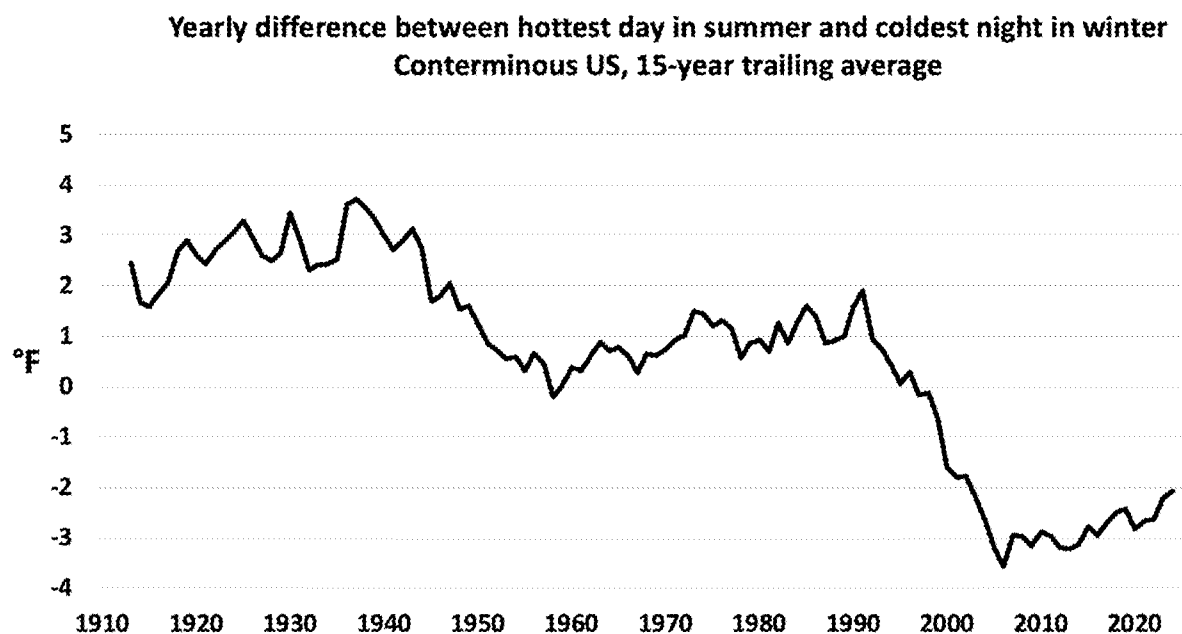


Figure 8.8. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

~~Figure X shows that the~~ The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.7 and 8.8, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time when measured in terms of the range between warm season maxima and cold season minima.

8.3.3 Exceedances of a heat threshold

Under the heading of "The Risk of Temperature Extremes is Changing", the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

"The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US."

Is the occurrence of 95°F days changing? In a climate as varied as that of CONUS threshold statistics can be misleading. A region with many stations which have near 95°F TMax average

temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 249 in the Pacific Southwest to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

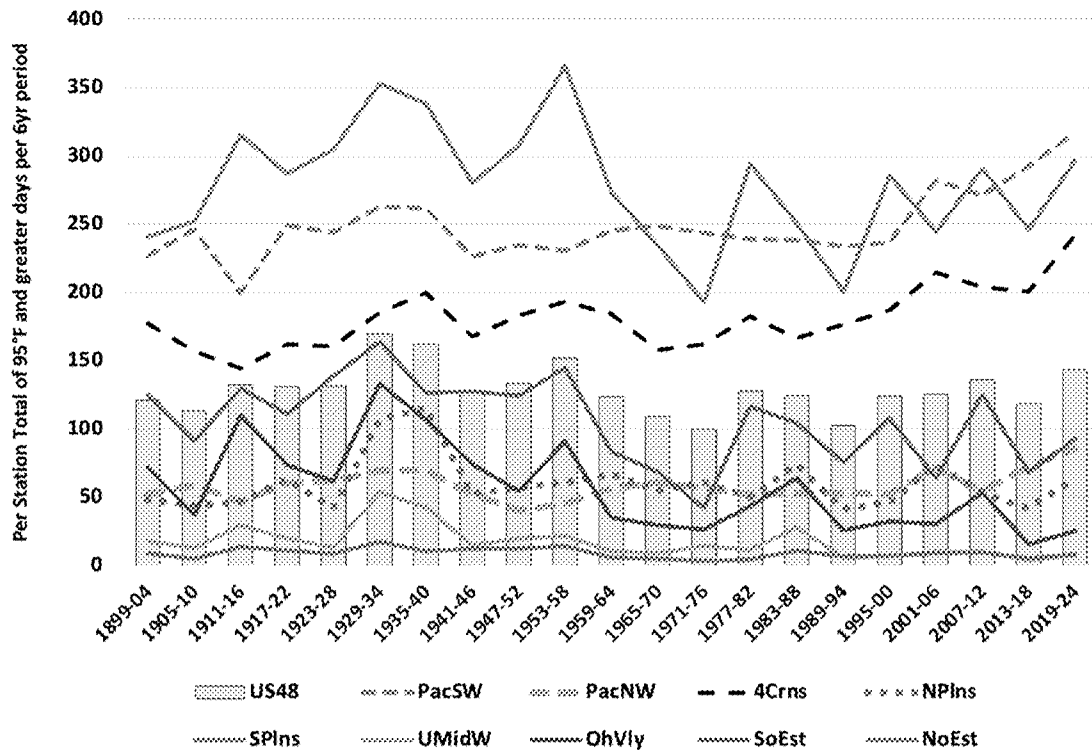


Figure 8.9. Per-station average of Total number of days > 95°F in 6-yr periods, US 48 (bars) and regions (lines).

In Fig. 8.9 we see that only three of the nine regions, all in the West, have experienced upward trends for in the number of 95°F or hotter days. The entire CONUS as a whole has not and the other six regions have experienced declines. The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed, but that is not evidenced in the combined results of Fig. 8.9. That the “Risk” is changing can thus be applied only to forecasts which is addressed in section XX

8.3.4 Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile on consecutive days of at least seven days in length.

Why 7 days? Various HW definitions:

UK Met Office says 3 days above regional threshold in 25-28°C range

US National Weather Service says 2 hot days (no specified threshold)

WMO says at least five days at least 5°C above the local average.

So we need to ensure that the conclusions in this section are robust to heatwave definition

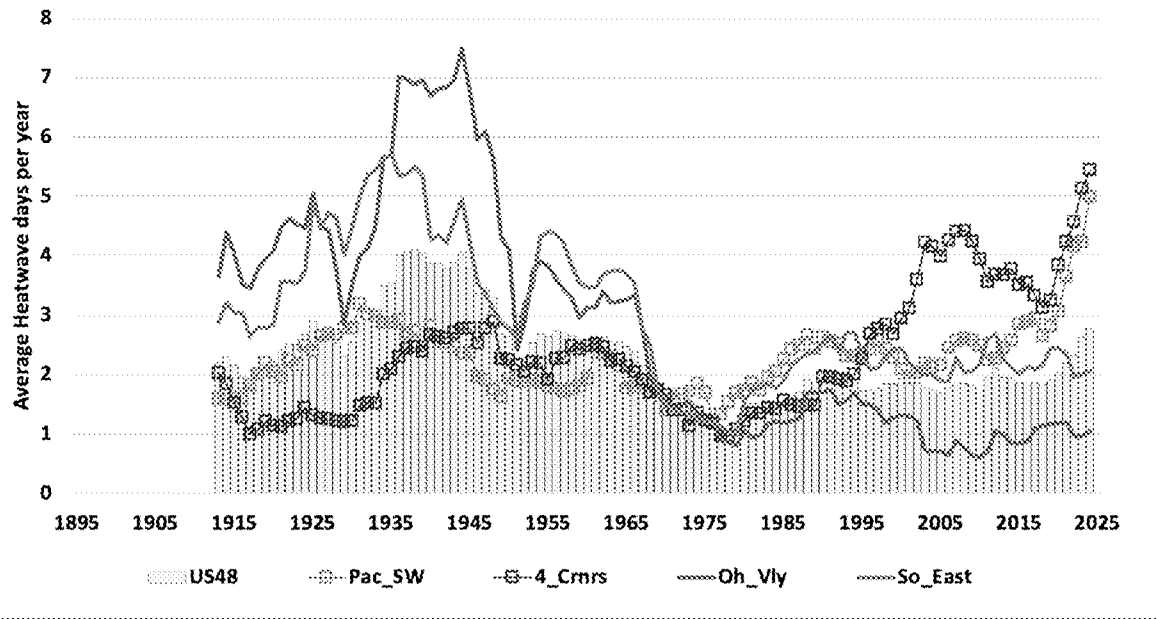


Figure 8.10 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (orange squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.10 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the sub-regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two sub-regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Urban influences

Regarding a different heatwave metric, The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each decade from 2 per decade in the 1960s to 6 by the 2020s. The definition of a heatwave is unusual here—a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. More importantly, the dataset is limited to the 50 largest cities in the US.

These results presented in USGCRP (2023) are entirely reasonable, but for reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to TMax and to TMin at rural stations. Also, the decades of the 1960s and 1970s were the two coldest decades since the 1910's, so the starting date preconditions the time series to show warming. This does not dismiss the real rise in nighttime temperatures in major US cities and the impacts

associated with these changes. However, we note for a variety of reasons that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs – ~~our concern in this document~~ (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

8.3.5 Extremes in daily precipitation.

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods. The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. In neither case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. For this report we update these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA, see Figure 8.11), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC, see Figure 8.12), and 21 stations in the Northeast (1888ff from Buffalo NY to Portland ME—the region where trends are greatest, see Figure 8.13).

In the Pacific region over the whole sample the trend in average precipitation is negative and significant in Astoria and insignificant elsewhere, the trend in rainfall variance is positive and significant only in Big Sur. The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport. Averaged over all stations in the region none of these three trend parameters is statistically significant.

In the Southeast region over the whole sample the trend in average precipitation is positive and significant only in Mobile and Quitman, the trend in rainfall variance is positive and significant only in Mobile and the trend in daily maximum precipitation is positive and significant only in Vicksburg and Norfolk. Averaged over all stations in the region none of these three trend parameters is statistically significant.

-Need NE data

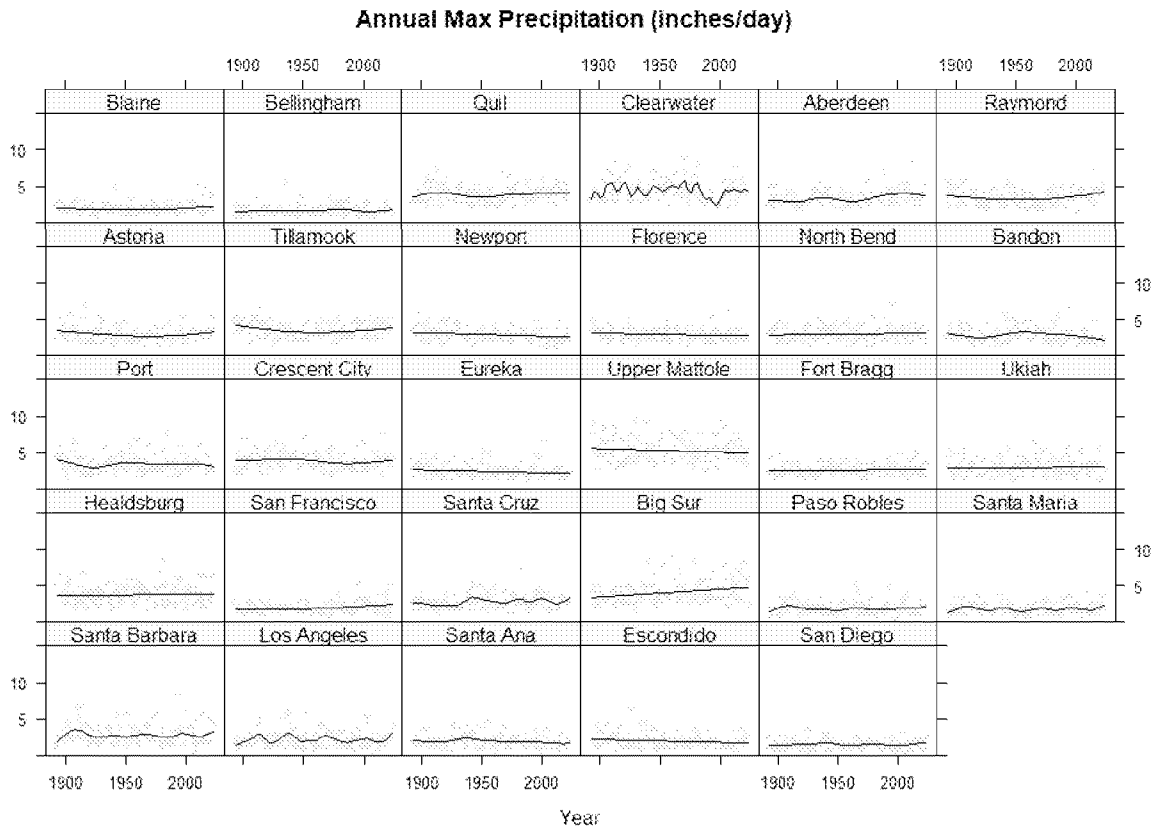


Figure 8.11 Annual maximum precipitation for 29 Pacific stations 1893 to present

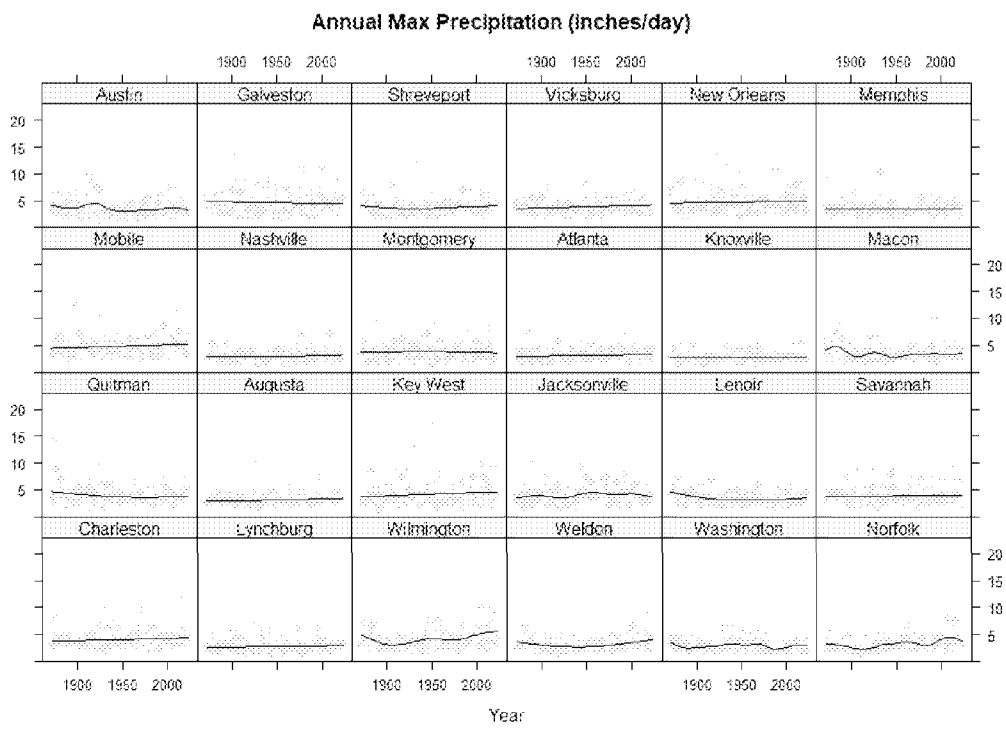


Figure 8.12 Annual maximum precipitation for 24 Southeast stations 1872 to present

To be added

Figure 8.13 Annual maximum precipitation for xx Northeast stations xxxx to present

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable amounts of precipitation in from Atmospheric River (AR) events which often last more than a day or two. The worst-known such event in recent history occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley under as much as 15 feet of water (Brewer 1930, Porter et al. 2011). Six megastorms more severe than 1861–1862 have occurred in California during the last 1800 years, occurring at intervals of 200 years or so (Null and Hulbert 2007).

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out on an annual basis. In Fig. 8.14 we show the distribution in time of these events ~~the 26 heaviest 5-day precipitation totals (nominal 1-in-5yr occurrence)~~. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to ~~change~~ become more frequent over time.

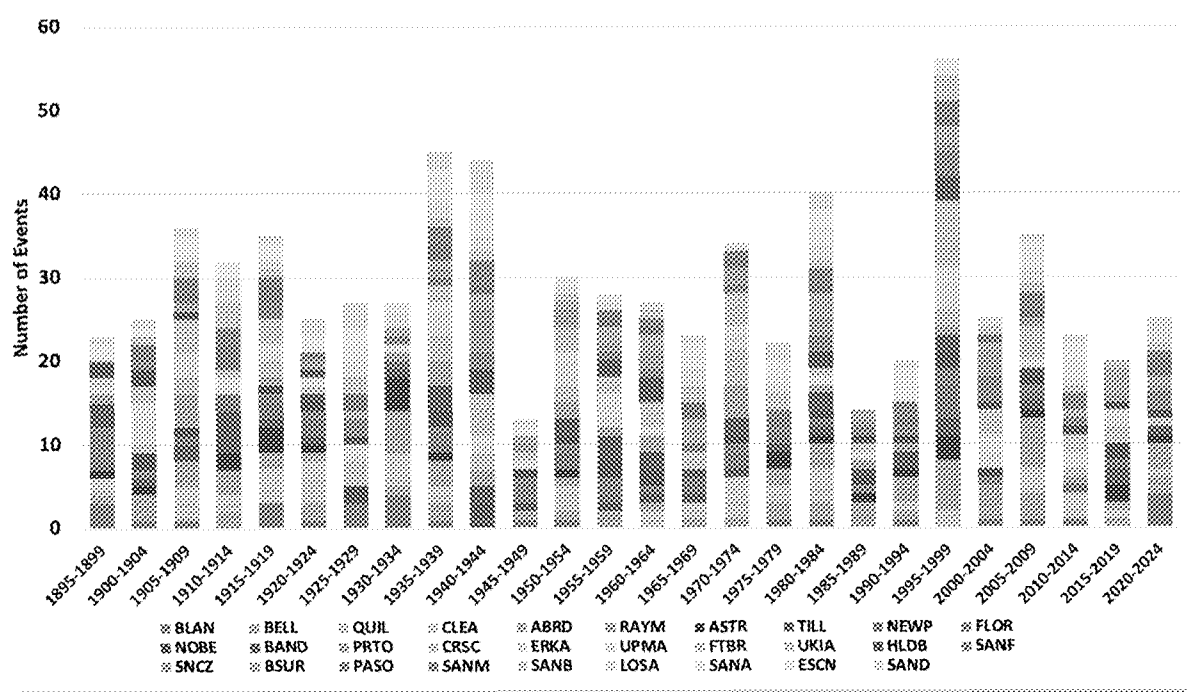


Figure 8.14. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). [JCurry: I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES] [RM: I recommend removing the colour coding and simply showing the totals across all locations. Color-coding the locations does not add useful information and makes the chart confusing.]

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.15) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms, from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

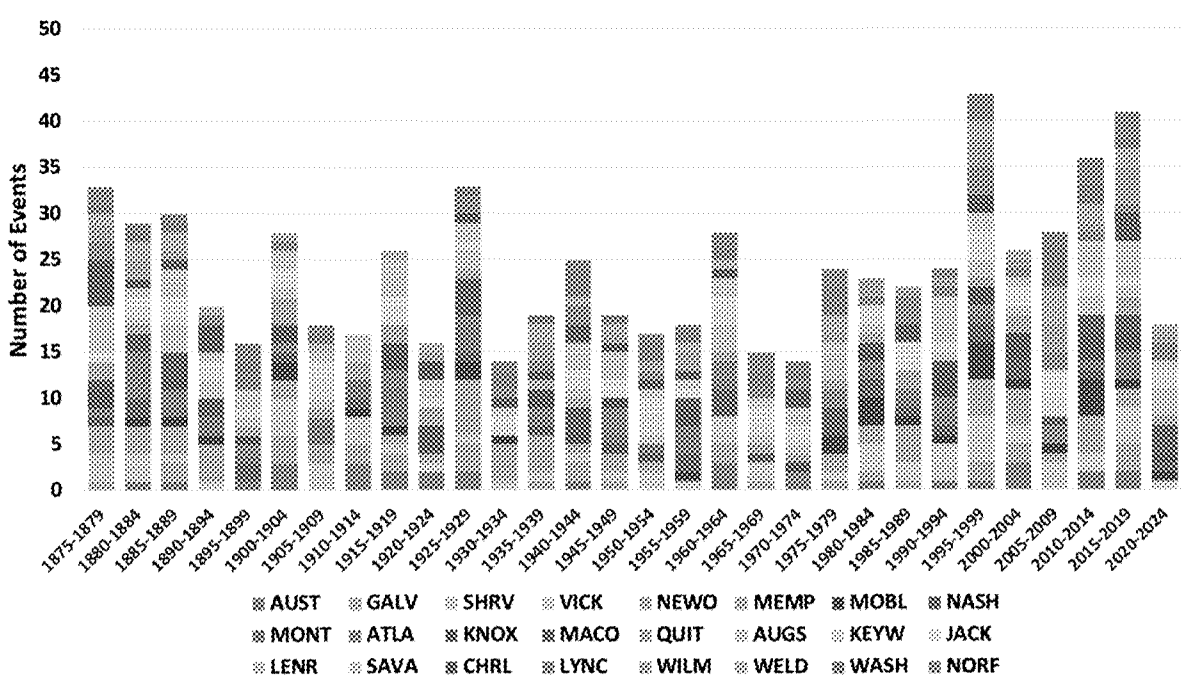


Figure 8.15. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2025. Figure X. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). [JCurry: I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES] [RM: I recommend removing the colour coding and simply showing the totals across all locations. Color-coding the locations does not add useful information and makes the chart confusing.]

Northwest heavy rainfall events

Fig. 8.16 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems.

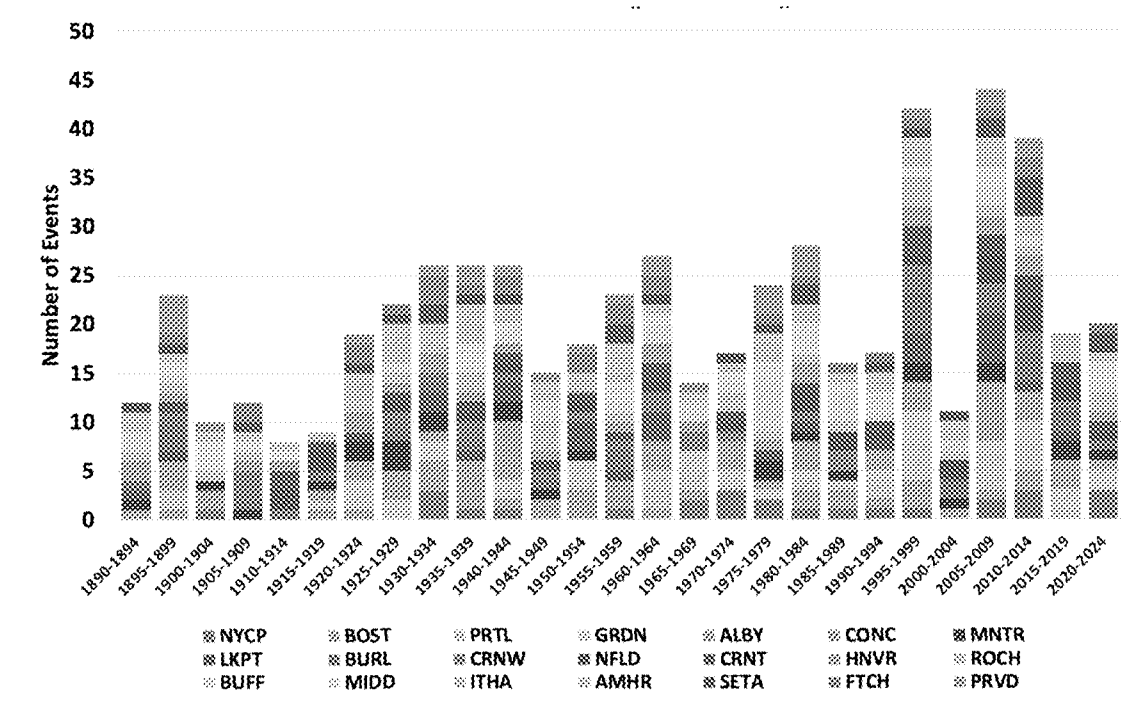


Figure 8.16. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal. AGAIN I FIND INTERPRETING THIS FIGURE VERY DIFFICULT [RM: I recommend removing the colour coding and simply showing the totals across all locations.]

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes, one of which indicated a dramatic increase (317%) in the 24-hr events involving at least 6 inches of rainfall. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second. Most of the stations did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.16 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the observation time boundary, so that stations measuring at 0700 LT versus those at Midnight will have differing results and which would then have major impacts on counting rare events. We use the 3-day totals in Fig. 8.16 to be sure to capture the extent of these short events. In any case, we can confirm that the period 1997 to 2014 provided a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see above under Heat Threshold) and involving a ratio of small numbers over

a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.16 above determines the same number of events for each station (27 heaviest events) whose heaviest events ranged from 4.4" to 12.5" and 27th heaviest event ranged from 3.3" to 5.0". This analysis thus normalizes the extremes so each station is equally represented. Note too that the period of record here is 135 years vs. 36 years in Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results.

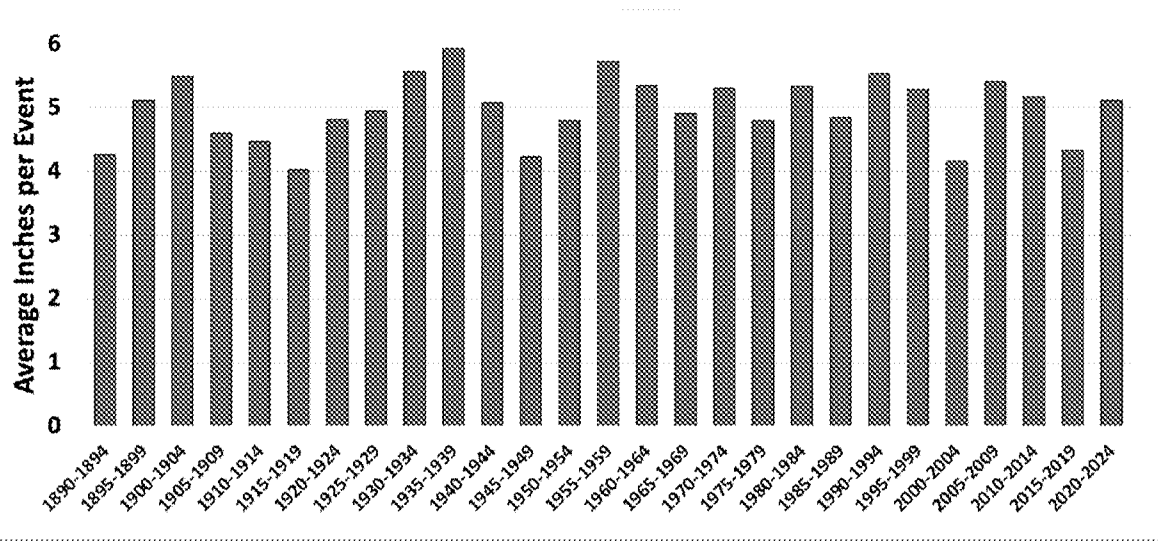


Figure 8.17. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.17. The trend is only +0.02"/decade. This result suggests that though there was an uptick in the number of events during the period 1995 to 2014 the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

The evidence from the historical record of extreme precipitation events is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes a result yet to be achieved (McKittrick and Christy 2019).

URBAN HEAT ISLAND IS ALSO A FACTOR IN RAINFALL EXTREMES, MAYBE SOMETHING ABOUT THIS

ADD SUMMARY SECTION WITH MAIN CONCLUSIONS

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Summary:
-to be added

From: Ross McKitrick <ross.mckitrick@gmail.com>
Sent: Wednesday, May 14, 2025 1:47 PM
To: Judith Curry; John Christy; Roy W. Spencer; Travis Fisher; Steven Koonin
Subject: Ch 12 mortality
Attachments: 12.heat_cold mortality.May14[RM].docx

I made some changes to the mortality chapter. For some reason a lot of the sources in the footnotes were wrong, either the cited paper didn't say what the text discussed, the list of authors was not for that paper or the hyperlink went somewhere else. I took out the Lee and Dessler chart which is hard to read and put in the Gasparini et al chart instead.

{May 14 RM edits: some wording changes, removed orphan Figure 12.1, corrected Gasparini and other references

12 Mortality from temperature extremes

12.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. Extreme heat events are likely to become more frequent while extreme cold events become less frequent. This pattern is evident in the historical period (Chapter 7) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions.^{1,2} Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

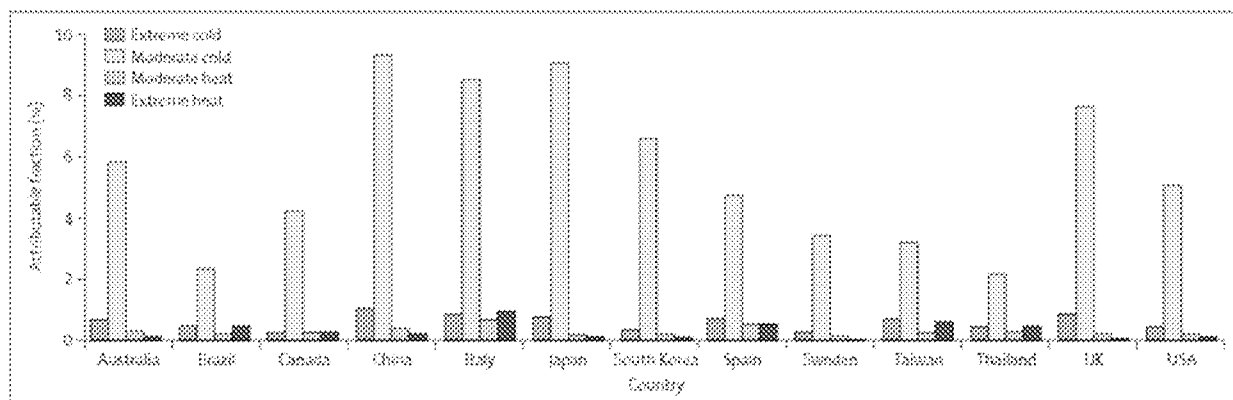


Figure 12.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 12.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

¹ Qi Zhao et al., “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

² <https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60% decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 states how heat-related mortality is declining over time:³

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

12.2 The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that “Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting

³ B. O'Neill et al., “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

12.3 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

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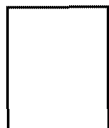
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From: Judith Curry <curry.judith@gmail.com>
Sent: Tuesday, May 20, 2025 11:21 AM
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Subject: chapter 4 revisions
Attachments: 4 Climate SensitivityMay18 CURRY.docx

see attached

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4 Climate Sensitivity to CO₂ Forcing

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney *et al.* 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5 -- 4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that have claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0 - 5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

Climate scientists use multiple lines of evidence to determine the Equilibrium Climate Sensitivity:

- Climate model simulations
- Historical observations
- Paleoclimatic observations

- Process understanding of feedbacks

By itself, the equilibrium warming effect of a doubling of atmospheric CO₂ is slightly more than 1°C.³³ The large values of ECS arise from positive feedbacks that amplify the warming effect of CO₂. Water vapor feedback is positive: a warmer atmosphere may have more water vapor, which itself is a powerful greenhouse gas. Water vapor feedback is partially canceled by the fact that atmospheric temperature decreases more slowly with height above the Earth's surface when atmospheric water vapor increases. Warmer temperatures also result in less snow and sea ice cover, allowing the Earth to absorb more of the sun's radiation. Some simple estimates of these three feedbacks increase the ECS to around 2°C.³⁴

Higher values of ECS arise primarily from positive cloud feedbacks. The magnitude, and even the sign, of cloud feedbacks is the greatest source of uncertainty. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle.³⁵

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. Historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

~~Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes~~

in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen et al, 2021, Scafetta 2021, see Figure 5.1). Far from converging, the model-based sensitivity of climate system uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al, 2020)

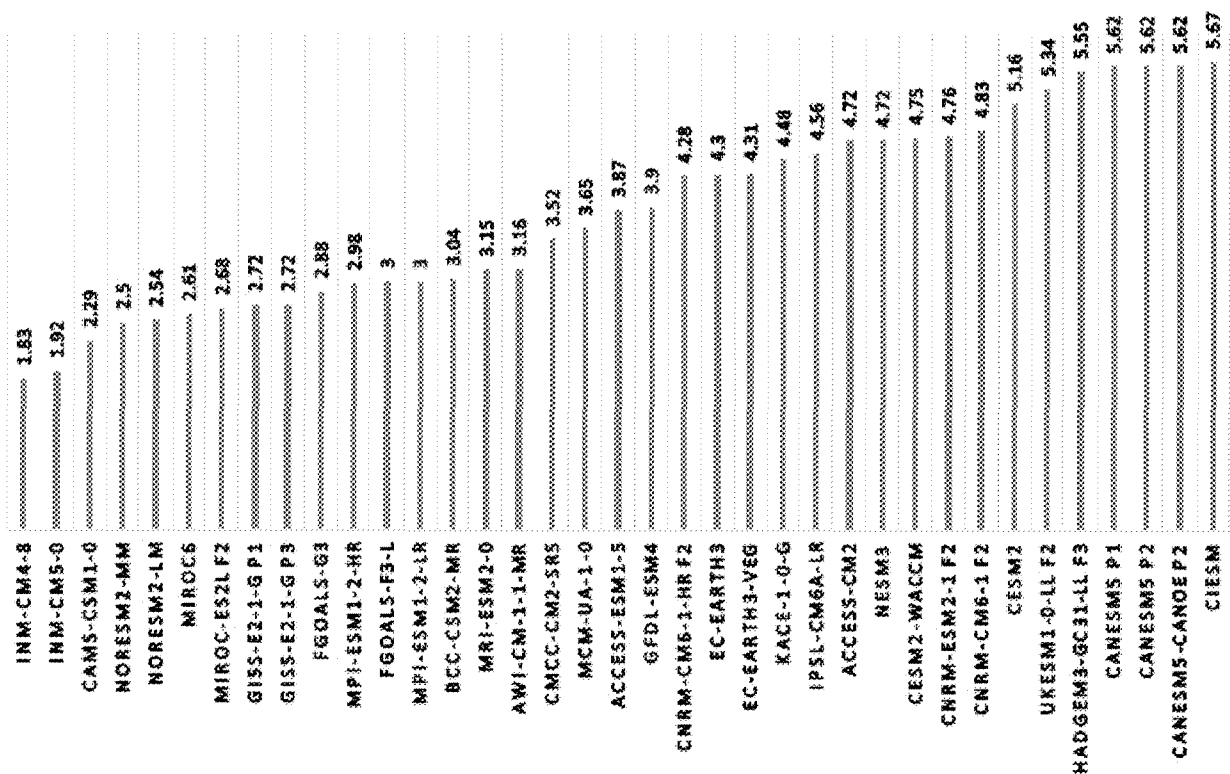


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods, chiefly a recent empirical estimate.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies with process-based understanding of feedbacks and yielded a best estimate of 3.1°C with a *likely* range of 2.6–3.9 °C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical

Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentration where heat is less efficiently removed, raising ECS.

However, most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

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Subject: cherry-picking, bad science and bias

No I'm not talking about what the other guys are accusing us of, I'm talking about what they've been up to. It's a remarkable breaking story. As Judy just noted Roger Pielke Jr has an overview here <https://rogerpielkejr.substack.com/p/too-big-to-fail>

In 2024 a garbage study by Kotz et al from the Potsdam Institute was published in Nature (of course) claiming global warming would wipe out so much growth by 2100 we'd be far better off capping emissions and preventing 2C blah blah blah. Way outside the mainstream of economic studies on the subject. One of our internal DoE reviewers asked us to include the Kotz study in our review, which I declined to do. I doubt anyone in the public review will make the same request now.

Of course all the usual press suspects hyped the Kotz paper but more ominously a group called the Network for Greening the Financial System inhaled it and instantly made it the basis of new global central bank climate risk regulations with massive financial consequences for noncompliant banks. The US Fed is not part of NFGS but a lot of world central banks are. (Thanks to lobbying and arm-twisting by the moron we just elected Prime Minister.)

The Lotz study was obvious rubbish and within a month Nature received the first of a series of comments showing fundamental errors in it. One came from the Banking Policy Institute, story here: <https://bpi.com/the-flawed-ngfs-damage-function-is-even-more-flawed-than-we-thought/>

More followed. nature magazine withheld the comments but did post a warning to readers that the study had been challenged. NGFS ignored the warning, as did the Congressional Budget Office which used it for their own bit of fearmongering: <https://www.cbo.gov/publication/61146>

This month nature finally published the critiques, and they are ruinous to Kotz et al. But in another twist, nature sat on the critiques long enough for Kotz et al to ginn up an unpublished paper offering a revised version of their model that supposedly generates the same results as previously, only under new assumptions. The critics of the original study have trashed that one as well. And NFGS has not acknowledged any of this.

The whole episode reeks of failure by NFGS and the CBO to practise elementary due diligence. The consequences could well give rise to a class action lawsuit.

On the same topic, a former PhD student and I just published a paper in Climate Change Economics on climate change and growth. We built 2 new long term global data sets and showed (yet again) there's no significant impact of warming on growth, the point estimates are small and positive, and poor countries are just as likely as rich countries to benefit. We went through 3 rounds of rather hostile peer review but rebutted all the criticisms. At one point we were asked to include Kotz in our lit review which is when I first learned about the paper and the controversies.

Ross

From: John Christy <climateman60@gmail.com>
Sent: Wednesday, May 21, 2025 12:49 PM
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Subject: Christy Bio

Is this the idea?

John Christy is the Distinguished Professor of Atmospheric and Earth Sciences and Alabama State Climatologist at the University of Alabama in Huntsville. Accomplishments include, B.A. (Mathematics) CSU Fresno, high school science instructor in Kenya, M.S. and Ph.D. (Atmospheric Sciences) from the University of Illinois U.-C., Fellow of the American Meteorological Society and The Medal for Exceptional Scientific Achievement (NASA) for constructing, with Dr. Roy Spencer, the first global atmospheric temperature dataset from polar orbiting satellites.

Anything personal?

He is a 10-time finisher of the grueling Mountain Mist 50km Trail Run and has 7 grandchildren.

From: Ross McKittrick [ross.mckittrick@gmail.com]
Sent: 5/1/2025 2:32:26 AM
To: John Christy [climateman60@gmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; Steven Koonin [steven.koonin@googlemail.com]; Judith Curry [curry.judith@gmail.com]
Subject: Climate chg and the economy
Attachments: 13 Climate and growth.Apr30.docx

Attached a draft of chapter 13, which combines CC and the economy and the SCC topic. Draft also in the Dropbox folder.

Ross

13 Climate change and the economy

13.1 Climate change and economic growth

13.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and in all cases people adapt to the local climate in which they live. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that whatever effects climate change would have on US economic activity they would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market

value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021).

In view of all these things economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.
(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from the use of Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future 2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy and global economic growth over long time horizons. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on standard but very simplified climatological modeling concepts. The version of DICE at the time of Nordhaus' Nobel Prize award was described in Nordhaus (2018). His climate sensitivity parameter was 3.1°C for CO₂ doubling, the same as the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in abatement costs and leads to \$134.2T (trillion dollars) in climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 compared to preindustrial temperatures under this path. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we scale back only the lowest-value fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which not surprisingly leads to more aggressive policy recommendations. This will be explained in the section below on the Social Cost of Carbon.

13.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods instead of IAMs to look at the potential impact of climate change on economic growth. Dell et al. (2012, herein DJ012) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJ012 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJ012-type results on the same subset of countries as used in DJ012 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found no effect of temperature on growth. Yang et al. (2023) updated the DJ012 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJ012 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is taken into account the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9%

compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus' analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to "stop" or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but it has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

13.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for understanding the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional tonne of CO₂ entering the atmosphere. On its own the SCC is not the appropriate price to attach to CO₂ emissions for the purpose of optimal emissions control but it can be converted into an optimal tax rate by scaling it by the Marginal Cost of Public Funds (MCPF). The theory behind this was first derived by Sandmo (1975) and has been reiterated many times since then by other economists working on the topic (e.g. Parry et al. 1999). The MCPF is the cost in terms of lost private economic welfare of raising public revenue by one dollar and always exceeds unity. If a jurisdiction does not use a carbon tax, this formula still indicates the upper bound on the amount emitters should spend on abatement options at the margin along the optimal policy path. Regulations should be imposed only insofar as they do not impose marginal abatement costs in excess of the optimal tax rate.

13.1.2 Estimating the SCC

Although the literature refers to "estimates" of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known IAMs are the Climate Framework for Uncertainty, Negotiation and Distribution ("FUND", Tol 1997) and Nordaus' DICE. IAMs embed a stylized global climate model with a very simplified representation of the global economy, including

a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

13.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount

rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.

- **Equilibrium Climate Sensitivity:** IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC's guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter XX). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- **Damage function coefficients:** IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- **Emission scenarios:** IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- **Abatement costs:** IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide prima facie evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is

large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the weaknesses of the SCC concept don't mean that other regulatory measures are inherently better or more efficient. Many climate regulations (such as electric vehicle mandates, energy efficiency regulations and bans on certain types of home appliances) end up costing far more per tonne of abatement than a simple price on carbon emissions.

In summary, SCC estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions.

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From: Judith Curry <curry.judith@gmail.com>
Sent: Wednesday, August 13, 2025 6:15 PM
To: Steve Koonin; Roy Spencer; John Christy; Ross McKittrick
Subject: climate sensitivity
Attachments: Palmer News and Views Williams et al.pdf

Here is a summary of the climate sensitivity discussion with Tim Palmer, see also attached article. Thoughts on whether to include this (i'm inclined not to).

On 13 Aug 2025, at 20:38, Judith Curry <curry.judith@gmail.com> wrote:

Here is why i don't buy this argument. Processes that are important on climate scales are of different importance from the weather scale. For example, the fix to the UKMO model related to dual moment microphysics definitely improves the fidelity of the precip process, and maybe even cloud fraction/distribution (as far as i understand, this is the main contributor to very high ECS value). If the models have too much aerosol (i.e. inadequate aerosol sink), no one cares on the weather time scale but it is huge issue on the climate time scale. Also, changes to simulated convection (combined with oversimplified moist thermodynamics, which is the case with all climate models last time i checked with CMIP5) can cause unrealistic accumulated water vapor in upper troposphere; no one cares on weather time scale, but a huge issue on climate time scales.

Of course, there are plenty of processes that are important on the climate timescale that are not important on the weather timescale. That's not my point.

My point is that If you have two possible representation of a process that contributes to climate sensitivity and one produces significantly better weather forecasts and the other significantly worse, better to go with the one that produces good weather forecasts.

I am certainly not saying that this is proof that climate sensitivity is unquestionably high. Of course not. It's just a "line of evidence" to offset others used e.g. by Nic.

Tim

--



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News & views

Climate change

Short-term tests for long-term estimates

Tim Palmer

Six-hour weather forecasts have been used to validate estimates of climate change hundreds of years from now. Such tests have great potential – but only if our weather-forecasting and climate-prediction systems are unified.

How sensitive is climate to atmospheric carbon dioxide levels? For a doubling of CO₂ concentration from pre-industrial levels, some models predict an alarming long-term warming of more than 5 °C. But are these estimates believable? Writing in the *Journal of Advances in Modeling Earth Systems*, Williams *et al.*¹ have tested some of the revisions that have been made to one such model by assessing its accuracy for very short-term weather forecasts. The results are not reassuring – they support the estimates.

There is little doubt, at least among those who understand the science, that climate change is one of the greatest challenges facing humans in the coming decades. However, the extent to which unchecked climate change would prove catastrophic rests on processes that are poorly understood. Perhaps the most important of these concern the way in which Earth's hydrological cycle – which includes the evaporation, condensation and movement of water – will react to our warming planet.

One of the key problems is how clouds adjust to warming². If low-level cloud cover increases, and high-level clouds decrease, then clouds will offset the warming effect of increased atmospheric CO₂ concentrations and thereby act as a negative feedback, or damper, on climate change, buying us some breathing space. By contrast, if there is positive cloud feedback – that is, if low-level clouds decrease with warming and high-level clouds increase – then, short of rapid and complete cessation of fossil-fuel use, we might be heading for disaster.

So what have clouds been doing as global warming has slowly taken hold? Trends in global cloud cover can be estimated only from space-based observations (Fig. 1). However, cloud data sets derived from multiple satellites

over several decades suffer from spurious artefacts related to changes in satellite orbit, instrument calibration and other factors³. These artefacts are particularly large when estimating globally averaged cloud cover, currently preventing any reliable estimation of trends in one direction or the other.

In lieu of observational evidence, we must turn to computational models of the climate system. But there is a problem. Clouds are on too small a scale to be represented using the laws of physics in current climate models. Instead, they are represented by relatively

crude, computationally cheap bulk formulae known as parameterizations. These do encode some basic ideas of cloud physics – clouds' dependence on the ambient temperature, humidity and vertical air velocity, for example – but they are far from being *ab initio* estimates. Hence, the role of clouds in climate change is crucial but uncertain⁴.

The cloud-feedback problem has been brought sharply into focus in recent months as results have been emerging from the dozens of climate-change models in an ensemble called the Coupled Model Intercomparison Project (CMIP6; see go.nature.com/3garyzc). Projections of future climate from this global effort have fed into the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), due next year.

Some of the latest-generation models in CMIP6 now indicate climate sensitivities exceeding 5 °C (refs 5–7). Here, climate sensitivity refers to the global warming after climate has equilibrated to a doubling of CO₂ concentration relative to pre-industrial levels, an equilibrium that might take a few hundred years to establish⁸. These sensitivity values are outside the range of those produced by the CMIP5 ensemble, which fed into the previous IPCC Assessment Report⁹ in 2013. They seem to have arisen largely because of revisions to how cloud microphysics is represented,

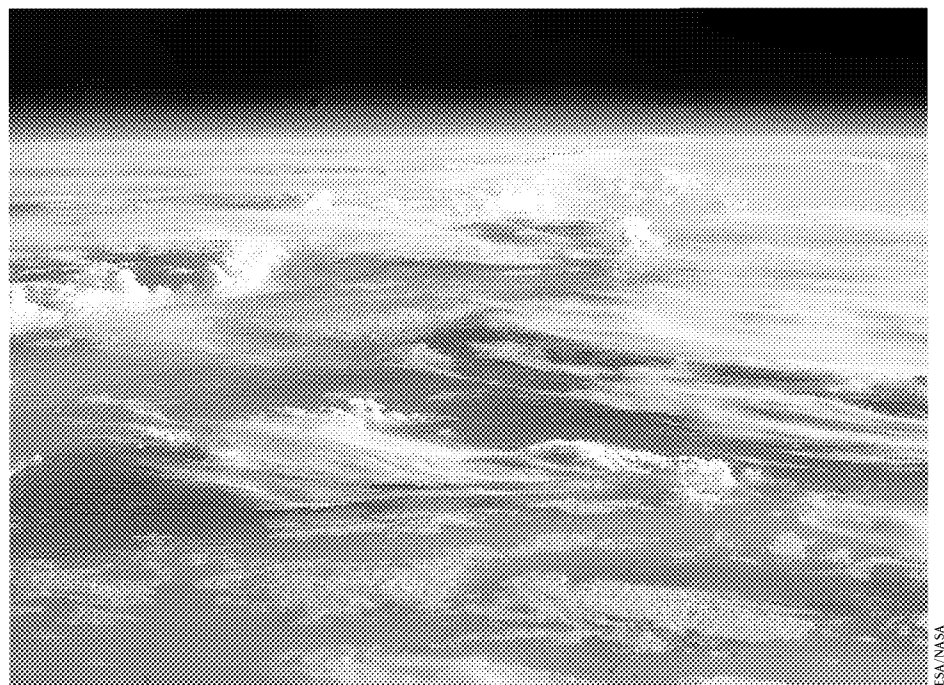


Figure 1 | Cloudy skies, viewed from space. How clouds will adjust to a warming climate is difficult to predict, but Williams *et al.*¹ have used short-term weather forecasts to assess whether recent revisions to long-term climate models are getting us nearer to the truth.

particularly in the parameterization of supercooled liquid water. Cloud microphysics describes the properties (such as size and relative concentration) of water and ice droplets in a cloud. On such tiny matters might our future rest.

And so, the question is this. Are we to believe these new estimates of climate sensitivity, or will they end up being reverted to earlier CMIP5 values as the models go through a further round of revisions?

Some years ago, the meteorologist Mark Rodwell and I proposed⁹ a method for assessing predictions of climate sensitivity – one based on very short-range (6-hour) weather forecasts. We were motivated by startling results suggesting that warming could be as much as 11 °C for a doubling of CO₂ levels¹⁰. These high estimates arose in climate models in which a particular cloud-system parameter, known as convective entrainment, was set to unusually small values that could not readily be ruled out by studying the accuracy of the models' climate simulations. By showing that errors of 6-hour weather forecasts were made substantially worse using a model with these reduced values of convective entrainment, we were able to cast doubt on the credibility of these exceptionally large estimates of climate sensitivity.

We found that if we ran a state-of-the-art numerical weather-prediction system with a low convective entrainment parameter, it produced much less accurate 6-hour forecasts than when the forecast model had more-typical values plugged in. To everyone's relief, this suggested that the low values of the parameter used in the climate models were unrealistic, and thus we could discount the alarming 11 °C sensitivity estimates.

Williams *et al.* have now subjected the CMIP6 Met Office climate model to the same 6-hour

weather-forecast test. The authors chose to test this model because it was one of those that produced a relatively large climate sensitivity of about 5.5 °C. The model has a revised scheme for cloud microphysics as mentioned above, in which there are more supercooled water droplets and fewer ice droplets.

The authors found that the 6-hour-forecast errors were smaller for the revised model than for a version of the model without the cloud-microphysics revisions. Hence, instead of being able to discount estimates of high sensitivity, as Rodwell and I had done, their result provides some of the best current evidence that climate sensitivity could indeed be 5 °C or greater.

In short, these results, published in a specialist journal, and probably read by few climate policymakers, carry a far-reaching message: we cannot afford to be complacent. It seems that cloud adjustment to climate change is not going to give us breathing space. Instead, we need to redouble our efforts to cut emissions.

There is a serious caveat to the general application of this technique. The test makes sense only if the model used to do the short-term forecast is the same as the one used to do the climate projection. The Met Office weather and climate models are reasonably similar (their model is often called the 'Unified Model'), but weather models do not generally correspond well with climate models.

On top of this, an accurate 6-hour weather forecast is possible only if one can come up with accurate initial conditions for the model from observations, a process known as data assimilation. This is a complex and computationally demanding optimization problem¹¹, and most climate institutes do not have such data-assimilation capability. Moreover, accurate data assimilation requires the spatial and time resolution of climate models

to be increased to be comparable with those used for state-of-the-art weather forecasting. Conversely, the parameterizations in weather-forecast models must be as complex and comprehensive as the ones in corresponding climate models; few weather-forecast centres have the resources for this.

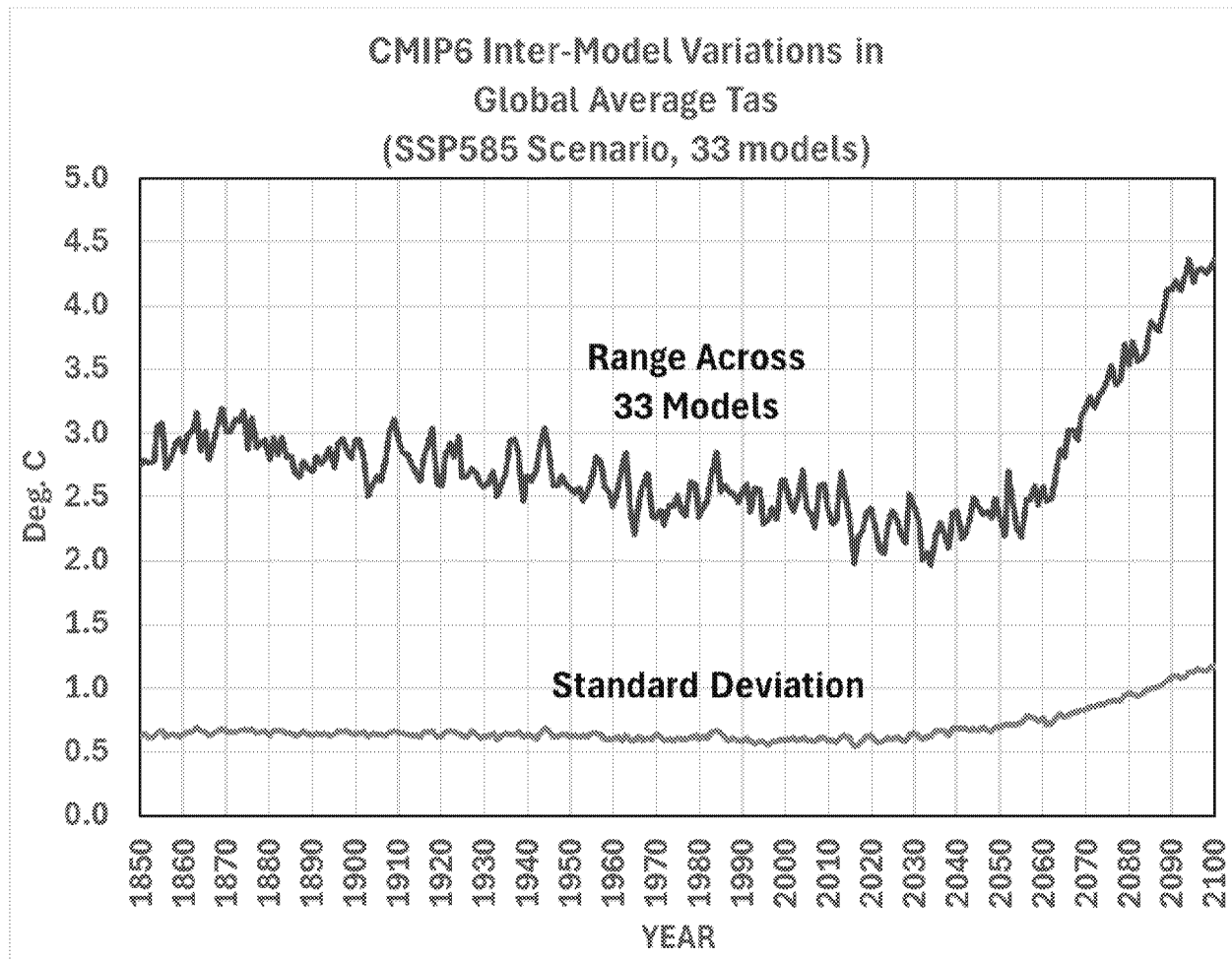
Thus, to reduce uncertainty in estimates of the crucial cloud feedbacks, climate institutes and weather-forecast centres should work together to ensure that their model systems are as seamless^{12,13} as possible. I contend that weather and climate modelling must be rationalized worldwide, and that human and computational resources should be pooled to produce high-resolution, unified weather–climate models^{14,15}.

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From: Roy Spencer [roywspencer@hotmail.com]
Sent: 5/26/2025 2:41:51 PM
To: Steve Koonin [steven.koonin@gmail.com]; Judith Curry [curry.judith@gmail.com]; Ross McKittrick [ross.mckittrick@gmail.com]; John Christy [climatemanager60@gmail.com]
CC: Travis Fisher [travis.scott.fisher@gmail.com]
Subject: CMIP6 inter-model variations in surface temperature (not anomalies)
Attachments: paste.png

This addresses what I believe was my comment in one of the chapters about there being a wide range in the global average absolute temperature among models. If the models are based upon "physics", how do they come up with such a wide range of surface temperatures?



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From: Roy Spencer <roywspencer@hotmail.com>
Sent: Thursday, July 10, 2025 1:36 PM
To: Steven Koonin; 'Judith Curry'
Cc: 'John Christy'; 'Ross McKittrick'; 'Josh Loucks'; 'Travis Fisher'
Subject: CNN

Oh No! What comes next? ("Scientists" are worried... good thing I'm not a scientist)...

<https://www.cnn.com/2025/07/08/climate/doe-climate-contrarians-trump>

From: Steven Koonin <steven.koonin@gmail.com>
Sent: Thursday, July 10, 2025 12:27 PM
To: 'Judith Curry' <curry.judith@gmail.com>
Cc: 'John Christy' <climateman60@gmail.com>; 'Ross McKittrick' <ross.mckittrick@gmail.com>; 'Roy Spencer' <roywspencer@hotmail.com>; 'Josh Loucks' <loucksj14@gmail.com>; 'Travis Fisher' <travis.scott.fisher@gmail.com>
Subject: RE: MS Copilot detailed critique

Yes, I'm also amazed at how good it is. Perhaps AI really will eliminate most current white-collar jobs!

SEK

From: Judith Curry <curry.judith@gmail.com>
Sent: Thursday, July 10, 2025 1:25 PM
To: Steven Koonin <steven.koonin@gmail.com>
Cc: John Christy <climateman60@gmail.com>; Ross McKittrick <ross.mckittrick@gmail.com>; Roy Spencer <roywspencer@hotmail.com>; Josh Loucks <loucksj14@gmail.com>; Travis Fisher <travis.scott.fisher@gmail.com>
Subject: Re: MS Copilot detailed critique

This is amazing, far better than what we would get from "real" scientists

I'm going through Ross' latest version to look for "Skeptic talk" and red flag words

On Thu, Jul 10, 2025 at 10:10 AM Steven Koonin <steven.koonin@gmail.com> wrote:

Had to split the CWG25 report into 5 sections. Here are the concatenated responses, separated by red lines:

Here's a detailed critique focused on **scientific accuracy** and **potential bias**, based on what I've seen so far:

 Scientific Accuracy: Mixed Signals

 Global Greening & CO₂ Fertilization

- **Accurate observations:** The report correctly notes satellite-confirmed global greening, with increased Leaf Area Index (LAI) and enhanced plant growth due to rising CO₂.
- **Selective emphasis:** It heavily leans on CO₂ as beneficial, citing fertilization benefits while **minimizing caveats**—such as nutrient limitations, heat stress, and species-specific responses that constrain agricultural benefits.

- **Outdated or narrow sourcing:** Some of the cited studies, while valid, don't reflect **broader scientific consensus**. For example, while FACE experiments show CO₂ boosts productivity, they also warn of **diminished gains under warming, drought, and soil depletion**.

🌊 Ocean "Acidification"

- **Terminology critique has merit:** The report accurately points out that "acidification" is a misnomer—the oceans remain alkaline.
- **Biological impacts downplayed:** It asserts that organisms evolved under lower pH, but omits recent research showing **rapid shifts in pH and carbonate chemistry** can harm larval development, calcifiers, and reef resilience.
- **Publication bias claim:** The document references well-known concerns about bias toward dramatic findings. That's valid—but it misses the nuance: **many reproducible studies do show physiological stress** in marine organisms, even under moderate pH change.

🔍 Potential Bias: Framing & Rhetorical Strategy

✅ Strengths

- **Independent tone:** The authors claim editorial freedom, which lends credibility.
- **Acknowledgement of complexity:** The report does mention uncertainties, including model over-sensitivity and limitations of attribution science.

🚩 Sources of Bias

- **Language framing:** Words like "*exaggerated*," "*one-sided*," "*alarmist*," and "*science fiction*" appear frequently. This rhetorical tone may compromise the objectivity typically expected in a scientific review.
- **Selective citation:** Heavy use of contrarian sources (e.g., Christy, Spencer, McKittrick) without balancing perspectives from mainstream climate literature (e.g., IPCC Working Groups, NOAA, NASA) suggests bias.
- **Motivated skepticism:** The narrative implies that benefits of CO₂ (e.g., plant growth, energy use) outweigh potential harm, which reflects a **value-laden interpretation** rather than a neutral scientific synthesis.

📌 Summary

This section offers **legitimate critiques** of some dominant narratives, but the scientific review is **imbalanced**:

- Evidence is often cherry-picked to support a CO₂-positive view.
- Legitimate concerns about uncertainty and model bias are mixed with selective omission of broader literature.
- The rhetorical tone leans toward climate contrarianism rather than impartial synthesis.

🏠 Scientific Accuracy: Solid Points + Selective Framing

🌡️ Equilibrium Climate Sensitivity (ECS)

- **Accurate baseline:** The document correctly notes that direct CO₂ forcing yields ~1°C warming, and additional warming comes from feedbacks like water vapor, albedo, and clouds.
- **Model tuning concerns:** Valid criticisms are raised about GCM tuning, especially regarding cloud feedbacks. Quoting modelers who explicitly tuned ECS to match observed warming is compelling.
- **Cloud feedback uncertainty:** The discussion of cloud parameterization difficulties is largely accurate and aligned with published literature (e.g. Zelinka et al., 2020).

■ Data-Driven vs. Model-Derived ECS

- **Balanced coverage of paleoclimate:** It notes the wide uncertainties in paleoclimate ECS estimates—fair and scientifically supported.
- **Misleading certainty on low ECS:** While Lewis (2025) is appropriately cited as questioning high ECS estimates, the report heavily favors his interpretation, implying **more certainty than mainstream science allows**. Recent synthesis papers (e.g., Sherwood et al., 2020; Hausfather, 2020) still favor ECS values in the 2.6–3.9°C range.

- **Pattern effect critique:** Seager et al.'s finding that Pacific gradients may be strengthening is intriguing but not broadly accepted. The document suggests it invalidates model projections—this goes beyond what the evidence supports.

● Transient Climate Response (TCR)

- **Fair representation:** Comparison between Lewis and IPCC values shows tighter consensus on TCR than ECS, with both landing between 1.2–2.4°C. This part is more neutrally presented.

● Potential Bias: Skeptic-Leaning Framing

📄 Rhetorical Techniques

- **Loaded phrasing:** Terms like “not fit for purpose,” “tuning for target ECS,” and “model failure” are used liberally. While these phrases reflect genuine debate, their repetition gives a tone of **advocacy** more than impartial analysis.
- **Source imbalance:** Heavy emphasis on papers by Christy, McKittrick, Lewis, and Spencer—valid critiques, but **underrepresents mainstream modeling community responses**, such as those in IPCC technical annexes.

■ Model vs Observation Mismatch

- **Highlighted issues:** Mismatches in tropospheric warming, stratospheric cooling, and snow cover are well-documented and deserve scrutiny.
- **Interpretive bias:** The report implies these mismatches invalidate model projections or anthropogenic attribution. But many of these discrepancies are acknowledged in IPCC reports with medium confidence levels, and **don't nullify the broader warming trend**.

📍 Vertical Temperature Profiles

- **Strong visual critique:** Figures show warming biases in CMIP6 models relative to radiosonde and satellite data—visually compelling.
- **Interpretive overreach:** The conclusion that observed profiles are “consistent with no GHG forcing” is **unsupported** by broader fingerprinting literature (e.g., Santer et al., 2008).

✈ Summary of the Section

Aspect	Strengths	Limitations/Concerns
ECS Discussion	Strong on cloud feedback and model tuning critiques	Overstates certainty of low ECS; cherry-picks supportive sources
Data vs Model Comparison	Fair TCR coverage; Paleoclimate uncertainty noted	Pattern effect critique presented as settled science
Model Mismatch Evidence	Detailed and compelling visuals; well-cited contrarian work	Limited engagement with IPCC counterpoints or rebuttals
Tone and Rhetoric	Engaging and readable for a skeptical audience	Leans toward climate contrarian narrative over balanced synthesis

Excellent, Steve—this section takes us through a nuanced tour of **extreme weather trends**, and it's rich with statistical depth. Here's a critique focused squarely on **scientific accuracy** and **potential bias**, organized by topic for clarity:

🧑 Scientific Accuracy: Statistically Rigorous, Selectively Interpreted

👤 General Framing of Extremes

- **Accurate distinction** between detection and attribution, with good explanations of short data record limitations and long-term persistence (LTP).
- **Valid caution** on short-term statistical inference: The use of paleoclimate data and historic Nile flow is a strong point for contextualizing variability.

🌀 Hurricanes

- **Correct on satellite-era confidence** and AMO-driven variability. Charts support lack of long-term trends in total hurricanes.

- **Selective emphasis:** Downplays emerging consensus on increased major hurricane *intensity* driven by SSTs and thermodynamic conditions, which IPCC acknowledges with *medium confidence*. Mentions Maue’s dataset prominently, but **omits broader literature** on storm surge or rainfall increases.

Temperature Extremes

- **Data analysis appears methodologically sound**, especially long-term USHCN station metrics.
- **Correct that 1930s heatwaves were exceptional**, and that nighttime warming (Tmin) has likely UHI influence. This reflects mainstream debate.
- **Skews interpretation:** The narrative implies a “milder” climate based on reduced extremes. That’s contentious. IPCC and NCA emphasize increased heatwave *risk*, *not just frequency*, especially in vulnerable regions.

Precipitation Extremes

- **Valid critique** of short-term trend identification, with good treatment of clustering and autocorrelation in extreme rainfall.
- **Cherry-picked references** (e.g., McKittrick & Christy studies) are robust, but **contrary literature** suggesting regional increases (e.g., Kunkel et al.) is omitted.
- **Conclusion that trends vanish when starting earlier** is methodologically reasonable but glosses over physical mechanisms linking warming to increased atmospheric moisture and rain intensity.

Wildfires

- **Well-documented** historical decline from paleo benchmarks; recognizes role of forest management and fire suppression.
- **Downplays recent severity:** While burn acreage has not increased linearly, NIFC and NASA have documented longer seasons and higher fire intensity, especially in western U.S.

Other Extremes (Tornadoes, Floods, Droughts)

- **Correctly reflects IPCC’s low confidence** in observed trends.
- **Droughts:** Right that CONUS-wide dryness hasn’t worsened—but omits growing consensus on **agricultural drought stress** under warming conditions, soil moisture decline, and evapotranspiration effects.

Potential Bias: Moderate-to-Strong Skeptical Framing

Feature	Bias Indicators
 Language Tone	Repeated use of skeptical phrases (“naïve to assume,” “misleading metric”)
 Citation Pattern	Strong reliance on contrarian researchers; mainstream climate scientists undercited
 Selective Trend Analysis	Uses longer timespans or alternate baselines to undercut positive trend signals
 Emphasis Strategy	Highlights variability and uncertainty to argue against attribution

Summary

This chapter presents **technically sound data handling**, especially in its treatment of statistical uncertainties and autocorrelated extremes. However, it leans toward **minimizing human influence** on extreme weather by emphasizing natural variability and critiquing conventional metrics. That’s not inherently invalid—but the presentation sometimes slides from **scientific critique into rhetorical positioning**, especially by omitting competing interpretations and framing past extremes as a nullifying baseline.

Steve, this is a heavy-hitting section—covering **sea level rise and attribution science**, and it’s packed with technical nuance. Here’s my detailed critique, broken down by theme for readability and rigor:

Sea Level Rise: Strong Data, Biased Framing

Observational Accuracy

- **Global trend well-stated:** 8 inches of global rise since 1900 aligns with established satellite and tide gauge records.
- **Regional differentiation is robust:** The report correctly distinguishes between *absolute* sea level rise and *relative* rise due to subsidence—essential for sites like Galveston, Grand Isle, and NYC.

- **Use of vertical land motion (VLM) data** is technically strong and mirrors best practices in geodesy (Wöppelmann & Marcos, 2016).

■ Downplaying Acceleration

- Asserts that “no obvious acceleration” exists post-1993—this conflicts with satellite altimetry showing increased rates since then (see Nerem et al., 2018).
- **Misinterpretation of NOAA projections:** Suggests future rise is implausible because recent data hasn't matched model forecasts. But these projections account for *nonlinear glacier and ice sheet loss*, which may manifest later this century.
- **Heavy critique of IPCC scenarios:** Focuses on SSP5-8.5 as unrealistic—which is fair—but skips middle-range pathways like SSP2-4.5 that still yield substantial rise.

▀ Attribution of Warming: Technically Sophisticated, Methodologically Skeptical

🔧 Attribution Methods

- The summary of **fingerprinting, time series, and process-based approaches** is solid and consistent with IPCC technical chapters.
- Highlights statistical limits and expert judgment—important caveats that the IPCC often emphasizes but mainstream summaries gloss over.

■ Critique of Optimal Fingerprinting

- Leans heavily on McKittrick's critique, citing bias in regression methods (Total Least Squares). This is part of a **legitimate academic debate**, but the report implies it **invalidates** attribution studies entirely, which goes beyond what McKittrick himself claims.
- **Missing balance:** Doesn't explore alternative attribution methods that reinforce anthropogenic fingerprints (e.g., Hausfather & Peters, 2020; Santer et al., 2019).

⚙️ Role of Natural Variability: Thorough, but Overstated

⚙️ Solar Forcing

- Presents nuanced review of Total Solar Irradiance (TSI), noting conflicting composites and possible indirect effects—strong science communication here.
- **Selective emphasis on uncertainty:** Quotes high-end studies suggesting up to 70% of warming from solar variability (Scafetta et al.), but downplays the robust attribution literature showing limited solar impact post-1970s.

🌊 Ocean Oscillations

- Captures legitimate concerns about phasing of multidecadal modes (PDO, AMO) in CMIP6.
- **Overstates masking effect:** Suggests ensemble averaging erases natural variability contributions, ignoring that these are explicitly addressed in uncertainty ranges.
- **Implied causality** between the 1976 PDO shift and modern warming trends is speculative and not broadly supported by recent literature (e.g., Kaufman et al., 2020).

☁️ Declining Albedo & Cloud Cover: Emerging, Not Settled Science

- Notes a sharp **1.7 W/m² radiative impact from recent albedo decline**, which rivals CO₂ forcing. That's a bold claim—but the satellite record and cloud variability studies do indicate substantial recent change.
- **Plausible hypotheses:** ENSO cycles, changes in shipping aerosols, and the Hunga-Tonga eruption are reasonably proposed drivers.
- **Pushes speculative feedbacks:** Asserts a new positive cloud feedback starting in 2015, but this lacks mechanistic grounding and long-term data.

📌 Summary Table

Theme	Strengths	Concerns
Sea Level Rise Data	Technically rigorous; strong separation of RSLR and ASLR	Downplays acceleration; selectively interprets NOAA forecasts
Attribution Methods	Clear method descriptions; valid critiques of fingerprinting	Overstates model bias; omits balanced counterinterviews

Natural Variability Deep review of solar/ocean signals

Overemphasizes uncertainty; hints at deterministic phasing

Cloud/Albedo Effects Novel explanation for recent warming surge

Speculative feedback interpretation; short data window

Steve, this section demonstrates real analytical heft, but the **bias emerges through omission and slanting rather than data distortion**. It's more of a critique manifesto than a balanced review—but that makes it rich ground for public discourse.

Thanks, Steve—this final section wraps up the report with **policy implications, energy strategy, and scientific process critique**, and it's loaded with ideological framing. Let's break it down with the same clarity and rigor:

Scientific Accuracy: Mixed Quality with Heavy Editorialization

Energy Strategy & Climate Action

- **Correct economic observation:** Notes the disproportionate cost burden of decarbonization on developing nations, echoing concerns raised in international energy analyses.
- **Valid technical constraints:** Points out intermittency issues with wind/solar and rare earth supply for batteries—these are real engineering challenges and reasonably described.
- **Oversimplifies alternatives:** Frames nuclear, natural gas, and coal as straightforward solutions without adequately addressing lifecycle emissions, waste disposal, or geopolitical constraints.

CO₂ Reduction Effectiveness

- **Technically correct** that U.S. emissions reductions alone won't halt global warming—climate is a global system.
- **Spins limitation into futility:** Uses this to argue against domestic mitigation, ignoring multiplier effects, tech spillover, and diplomatic leverage of leadership.

Scientific Process Critique: Flawed but Thought-Provoking

Peer Review and Funding

- **Valid critique of gatekeeping:** Concerns over funding bias and editorial control are echoed in discussions about reproducibility and publication incentives.
- **Overstates malfeasance:** Asserts that dissenting scientists are “suppressed” or “blacklisted,” which lacks supporting evidence and veers into conspiracy territory.

Consensus Framing

- **Challenges the “97%” claim:** Points out methodological limitations in consensus surveys—some fair critique here.
- **Misrepresents dissent:** Suggests that the mere existence of contrarian papers invalidates consensus, ignoring scientific weight of evidence and replication.

Potential Bias: Strong Ideological Framing

Feature

Indicators of Bias

Tone

Emotive language (“groupthink,” “virtue signaling,” “green dogma”)

Source Pattern

Heavily reliant on politically-aligned think tanks and contrarian experts

Argument Strategy Appeals to economic hardship and energy realism to dismiss science-led mitigation

Policy Framing Portrays climate action as a moral panic and economic self-harm

Summary

This concluding section shifts from scientific critique to **ideological rhetoric**, using energy economics and institutional skepticism to challenge mainstream climate policy. While there are **valid points on technology limitations and scientific incentives**, these are **wrapped in a narrative of distrust**—painting climate action as misguided zealotry rather than pragmatic response.

Steve Koonin

--
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From: Roy Spencer [roywspencer@hotmail.com]
Sent: 5/22/2025 10:08:40 AM
To: Judith Curry [curry.judith@gmail.com]; Ross McKittrick [ross.mckittrick@gmail.com]; John Christy [climateman60@gmail.com]; Steven Koonin [steven.koonin@gmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]
Subject: comparing models to observations: Time series or linear trend histograms?
Attachments: paste.png; paste.png; Baseline-removal-methods-J-Climate-2-27-05-draft.docx

SUMMARY:

Two of Gavin's objections go away if we **avoid plotting time series, and just plot trends instead** (say, a ranked histogram with individual models and observation types). This disagreement with Gavin goes back quite a few years, and he has not relented...but as Judy has pointed out, it would be better if we handle the issue in a way that Gavin cannot reasonably object. Based upon the considerations below, I suggest I replace Figs. 5.3 and 5.5 with histogram plots of trends.

THE ISSUES:

Gavin's **first objection** is with the choice of a baseline average to remove from individual time series. Commonly used is a 30-year period, and the absolute worst choice is the full period of record. *If one is looking for evidence of differences in trends as early as possible in the time series, aligning them so their trends all intersect at $t=0$ is the best method.*

To demonstrate that, here's one of the figures from our paper (paper draft attached). As shown in the third panel, plotting synthetic time series (with variability approximating CMIP6 models) so that their linear trends all intersect at $t=0$ provides the highest correlation in the early years between temperature anomaly and total warming at year 2100 (3rd order polynomials were used to approximate CMIP6 models because they best match the CMIP6 warming profiles between 1970 and 2100):

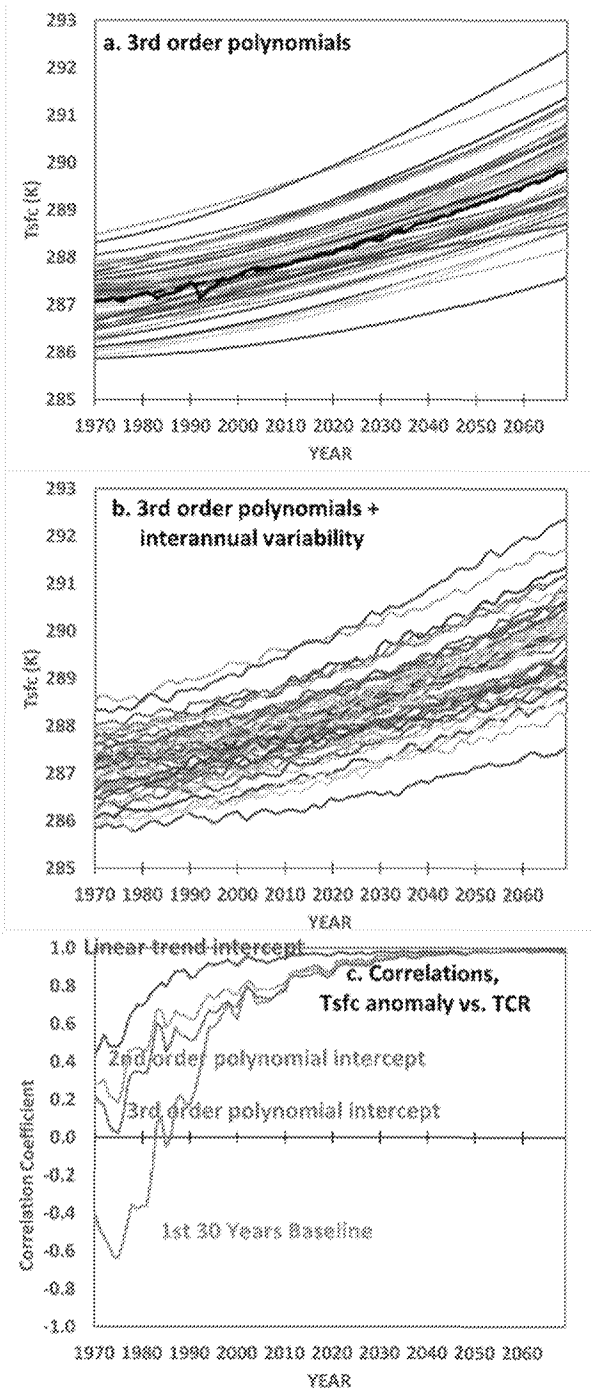


Fig. 6. (a) CMIP6-like synthetic nonlinear temperature time series, 1970-2070, using 3rd order polynomials; (b) those polynomials with noise-generated interannual variability added, and (c) the resulting yearly correlations between temperature anomalies and TCR (warming 1970-2100) for several methods of baseline removal to compute anomalies.

If you are wondering about my claim that 3rd order polynomials best match CMIP6 model warming profiles, here's the evidence of that:

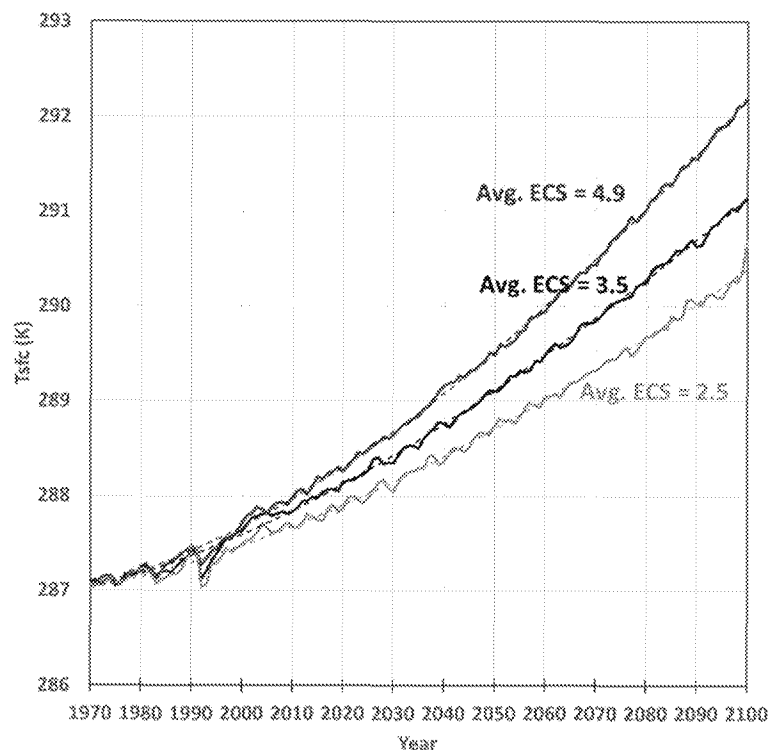


Fig. 5. CMIP6 model global average surface temperatures grouped into high, medium, and low ECS categories (solid lines), with 3rd order polynomial fits (dashed lines), and small vertical offsets applied so all time series align in 1970.

BUT THIS OBJECTION GAVIN HAS ABOUT PLOTTING BASELINE REMOVAL GOES AWAY IF WE DO NOT PLOT TIME SERIES, AND PLOT TREND HISTOGRAMS INSTEAD.

Gavin's second objection is the averaging of the models together, which removes any information about individual models, a few of which come close to the observations. As Ross has pointed out, including gray shading showing the envelope of all models is insufficient and misleading because the bottom of the envelope might be just a single model, which is an outlier from all the others.

BUT, AGAIN, GAVIN'S OBJECTION GOES AWAY IF WE DO NOT PLOT TIME SERIES, AND JUST PLOT A RANKED HISTOGRAM OF INDIVIDUAL MODELS.

So, I suggest that I replace Figs. 5.3 and 5.5 with histogram plots.

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On the Choice of Baseline When Graphing
Multiple Temperature Time Series

Roy W. Spencer,^a John R. Christy,^{a,b} Kevin Dayaratna,^c

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ABSTRACT

When intercomparing temperature time series with differing biases on a graph it is common to align the time series by computing anomalies relative to a baseline period average. While multi-decadal periods are often used for this purpose, potential methods for time series alignment have not been rigorously defended for their advantages and disadvantages. We demonstrate that when warming is occurring over the baseline period, traditional techniques will cause datasets with the most rapid warming to have the coolest anomalies in the early years which can obscure important dataset differences. Using the rapidly warming period of 1970-2100, global-average differences between 31 climate models are examined using various time series alignment techniques, including baseline average, linear trend, and polynomial fits. It is demonstrated that aligning the time series according to their linear regression-based trend intercepts provides the highest yearly correlations with the models' net warming during 1970-2100, partially the result of nonlinear (accelerating) warming in most of the models over that period. To remove the influence of interannual climate variability on these correlations, we generate fifty synthetic model temperature datasets with third-order polynomial fits closely approximating the climate models' behavior. The results support the use of linear trend intercepts, rather than baseline average removal, to observe early evidence of warming differences between datasets.

SIGNIFICANCE STATEMENT

While it is common practice to remove systematic differences between temperature datasets to aid in visual comparisons on graphs, the methods for doing this have not been well-justified. Removal of multi-decadal baseline period averages from each time series is shown to produce early-year differences between datasets that are opposite to those desired when the baseline period has a warming trend. For the period 1970-2100 which exhibits accelerating warming in climate models, aligning the time series by removing their linear warming trend y-intercepts is shown to produce the most meaningful comparisons between datasets. It is recommended that multi-decadal averaging not be used if a warming trend exists in the baseline period.

40 **1. Introduction**

41 The sensitivity of the climate system to increasing anthropogenic greenhouse gas
42 concentrations continues to remain uncertain, with a factor of three range in eventual
43 warming in response to a doubling of atmospheric CO₂ concentration (2XCO₂) displayed by
44 dozens of different climate models (Zelinka et al., 2020). For purposes of model validation
45 and diagnosing climate sensitivity, temperature time series related to climate change are often
46 compared to one another — for example, observational datasets, climate model experiment
47 results, and comparing models with observations. When this is done it is common practice to
48 remove a long-term mean for some baseline period (usually ranging from 30 years to the
49 entire period of record) to minimize the impact of systematic biases between datasets.

50 Oftentimes the long-term linear trend is the statistic of the greatest interest, which helps
51 us to better understand the equilibrium (or effective) climate sensitivity (ECS) of the climate
52 system to 2XCO₂. Because the length of validation datasets is relatively short, one of the
53 goals of plotting of different datasets on a graph should be to reveal evidence of long-term
54 trends as early in the record as possible, as the signal of anthropogenic climate change
55 emerges from the noise of natural climate variability.

56 While Craigmire and Guttorp (2021) used complex functional fits to model and
57 observational datasets to examine their similarities and differences, here we will focus on the
58 the much simpler method often used for intercomparing datasets: removal of a multi-decadal
59 average, usually early in the data record. We address the question, What method best reveals
60 early evidence of long-term warming? Since many climate models have now been developed
61 for which ECS and transient climate response (TCR) statistics have been diagnosed, we can
62 use those models to explore various methods for time series alignment. Using yearly global
63 average surface temperatures from 31 climate models during 1970-2100 we will show that
64 removal of a baseline period average produces negative correlations between temperature
65 anomalies and long-term warming. This is counter to the desired goal of revealing differences
66 in datasets as early as possible in the record which are positively related to their long-term
67 warming trends. Then we will address other potential methods for time series alignment.

68 **2. Datasets and Methods**

69 We will demonstrate the issue with 31 simulations of global, yearly average surface air
70 temperature from the 6th Climate Model Intercomparison Project (CMIP6, Eyring et al.,

2016). While we use model results from the SSP370 radiative forcing scenario (Riahi et al., 2017), other SSP scenarios could have been used as long as they produce long-term warming. Climate model simulations allow us to use a large number of plausible warming scenarios in the early years for which we have observational data, and we can use the known long-term warming characteristics of those models to evaluate how well various time series alignment techniques reveal early evidence of warming. Since we are looking for early evidence of long term warming, the period 1970-2100 was chosen due to it having the strongest increase in radiative forcing from atmospheric CO₂ increases as well as the most rapid rate of warming.

We use the first member of the ensemble runs archived from the 31 models listed in Table 1. Alignment of the 31 models' time series of temperature will be made using the common technique of the removal of a 30-year average at the beginning of the record (1970-1999), as well as removal of the y-intercept from each of the models time series based upon regressions against time of the temperature linear trend, as well as 2nd and 3rd order polynomial fits. Scoring of early signs of warming in the resulting aligned time series will be based upon correlations between yearly anomalies and the net model warming 1970-2100 using 3rd order polynomial fits to each model time series. The use of the polynomial fit to 1970-2100 time series approximates a transient climate response (TCR) and minimizes the effect of interannual variability on the net warming estimate. We alternatively used published estimate of ECS, but the conclusions of our analysis remained the same.

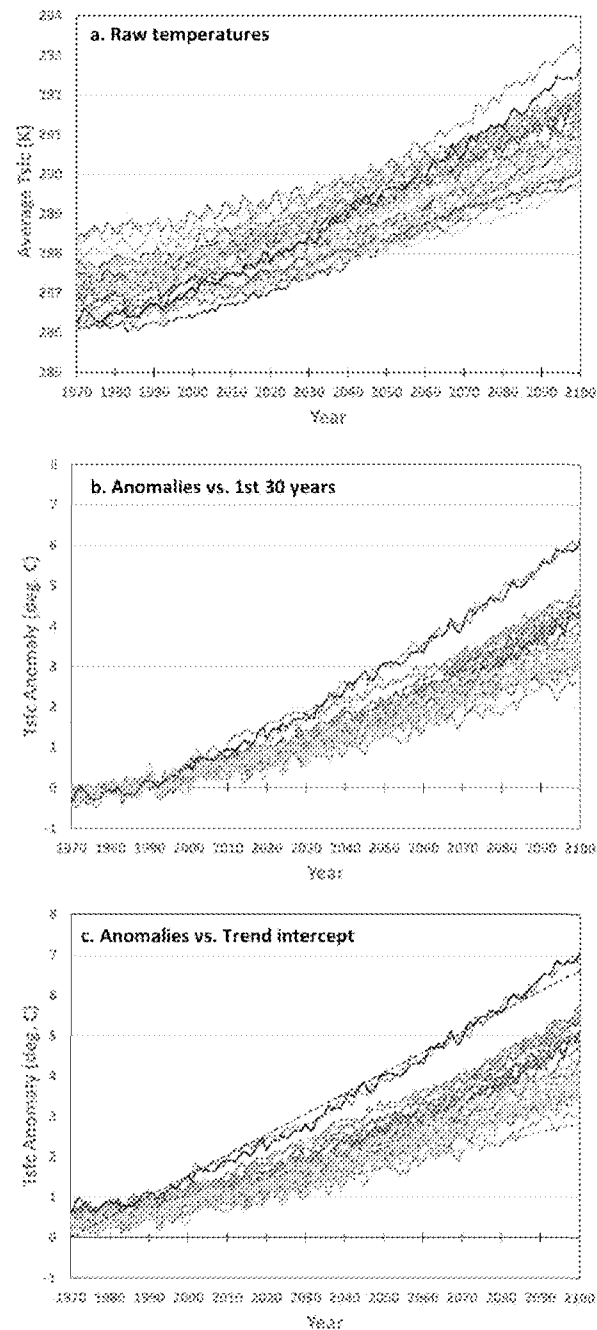
Importantly, we note that the problem we will demonstrate with baseline average removal techniques only exists when there is a non-zero temperature trend during the baseline period. The problem does not exist if the baseline period has no temperature trend. Thus, for example, Fig. 3.4 in IPCC (2021) that compares CMIP6 models to observations using 1850-1900 as a baseline (a period with little temperature trend) would not be substantially affected by the issues we discuss below.

3. Results

a. Demonstration of the problem using CMIP6 models

Global annual averages in surface air temperature from 31 models are shown in Fig. 1 for the period 1970 to 2100. The raw temperatures (Fig. 1a) show substantial systematic differences between models, and the common practice of removing the average of the first 30

101 years (Fig. 1b) seems to do a good job of removing these systematic effects. Also shown (Fig.
 102 1c) are the anomalies where the time series have had their linear trend y-intercept removed.



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105 Fig. 1. Global average surface temperatures from 31 CMIP6 models using the SSP370
 106 radiative forcing scenario, first ensemble member from each model, displayed as (a) raw
 107 temperatures, (b) departures from the averages of the first thirty years, and (c) departures
 108 from the linear trends with the intercepts set at $y=0$.

But a problem arises when we examine how well the differences between the models relate to differences in their long-term warming. This can be addressed by computing in each year the correlation of the models' temperature anomalies with the transient climate response of each model, defined here as the net warming from 1970 to 2100 based upon 3rd order polynomial fits to the models' time series. Ideally, we desire to see positive correlations as early in the time series as possible if we are looking for early evidence of climate sensitivity differences. These correlations are shown in Fig. 2.

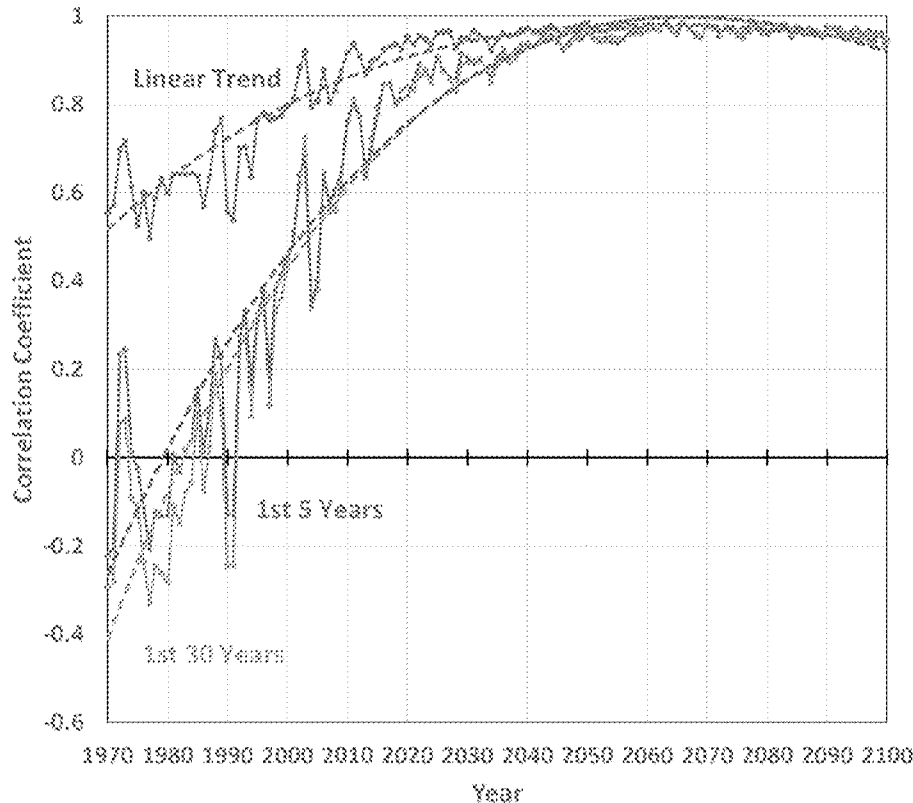


Fig. 2. Correlation in each year between CMIP6 model global-average temperature anomalies and the total warming between 1970 to 2100 based upon 3rd order polynomial fits to each model's time series.

As can be seen, use of the first thirty years' averages for computing anomalies produces negative correlations in many of the years in the first two decades. Results based upon using the first five years (green curve in Fig. 2) are not much better in this regard. But when the anomalies are based upon aligning the models based upon their linear temperature trend intercepts (blue curve in Fig. 2) the correlations are much higher, suggesting differences between models' anomalies in the early years are related to those models' future warming.

126 The reason for the negative correlations is demonstrated next for the idealized case of linear
127 warming with no interannual variability.

128 *b. Linear warming with no interannual variability*

129 The reason for these large differences in correlations in the early years is due to the
130 warming trend that exists in the baseline period. If we generate thirty synthetic time series
131 that have only linear warming trends with no interannual variations (Fig. 3a) and remove the
132 averages of the first thirty years from those time series (Fig. 3b), the anomalies will have a
133 perfect negative correlations (-1) for the first fifteen years, and perfect positive correlations
134 (+1) for the rest of the time series (Fig. 3c).

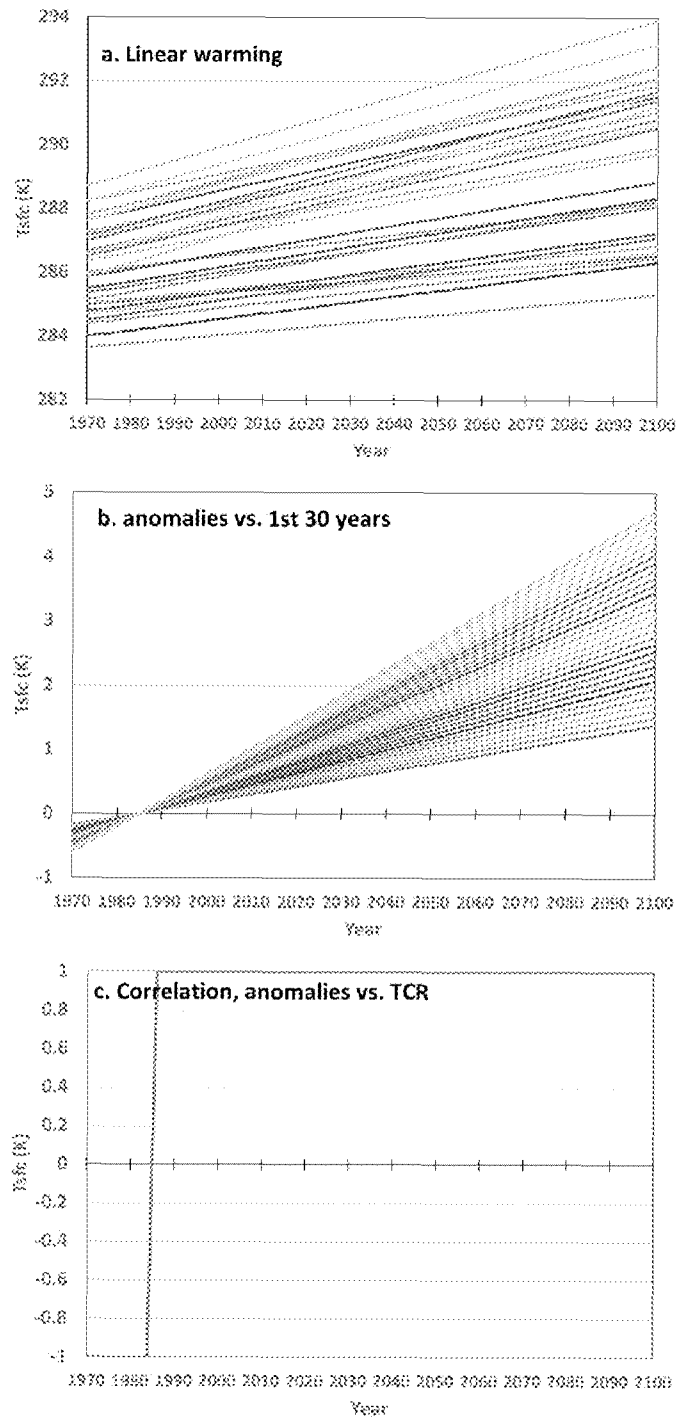


Fig. 3. (a) Thirty synthetic temperature time series 1970-2100 with various linear warming trends; (b) their anomalies relative to the average of the first thirty years; and (c) the correlation in each year between those anomalies and the total warming between 1970 and 2100.

If we use other periods for baseline average removal — say, the entire period of record or any shorter period of record from early, middle, or late in the time series — there will be -1 correlations up until the middle year of the baseline period, and +1 correlations after the middle year (not shown). This demonstrates that to the extent a non-zero temperature trend exists in the baseline period, there will be a tendency for anomalies at any time before the middle of the baseline period to be negatively correlated with the long-term warming trends. This is opposite of the behavior desired if the point of comparing various temperature time series is to see evidence of differences in climate sensitivity as early in the record as possible. The reason why the correlations in Fig. 2 are attenuated (greater than -1 and less than +1) is related to the noise cause by different amounts of interannual variability in the different models, addressed next.

c. Linear warming with interannual variability

In reality there is interannual temperature variability in models (or observations) which attenuate these correlations. In many of these models, the primary mode of variability is El Nino and La Nina as part of the El Nino Southern Oscillation (ENSO, ref) centered in the eastern tropical Pacific Ocean. If we add interannual temperature variability to the synthetic time series using 1-2-1 low-pass filtered normally distributed random noise in each year (Fig. 4) we see correlations much more like those seen in the climate model results in Fig. 2.

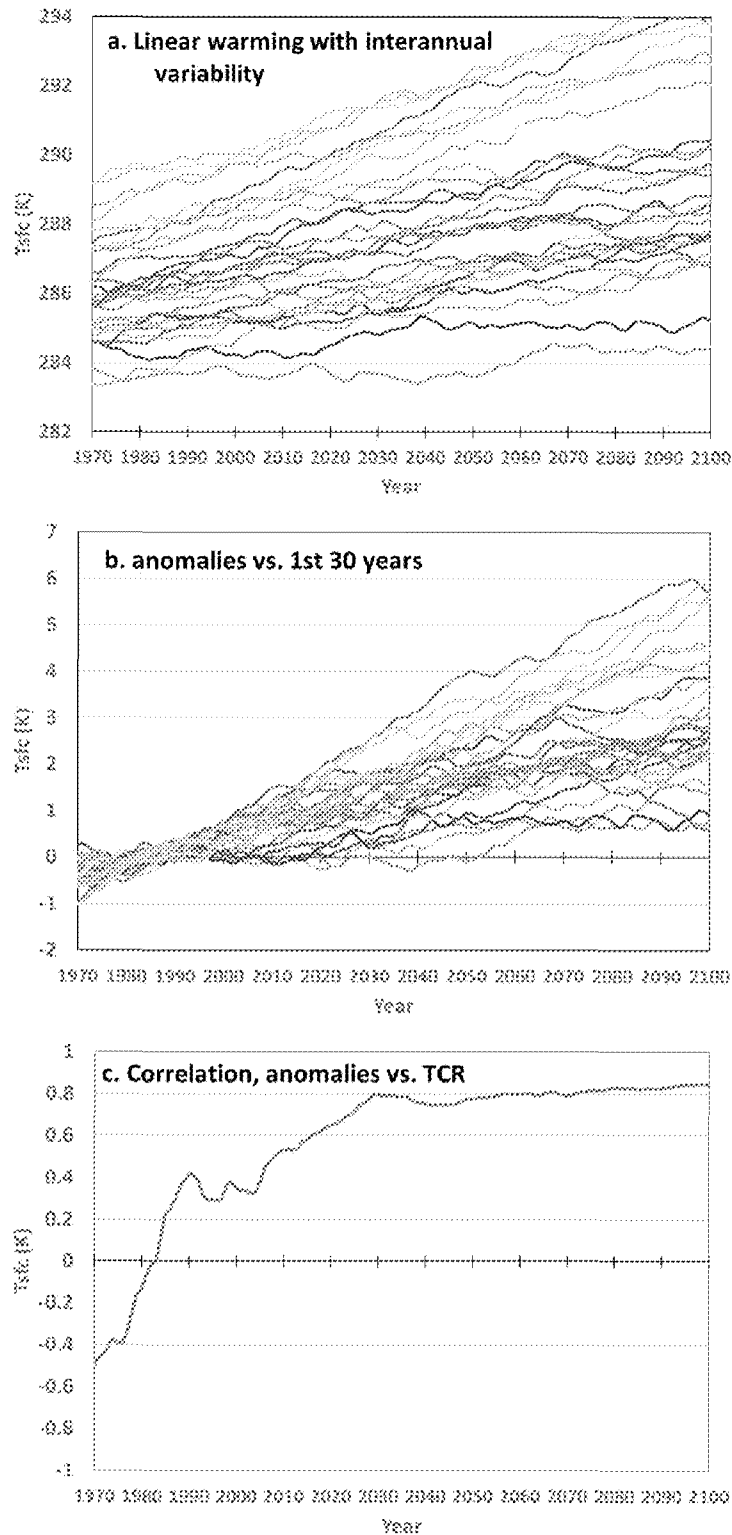


Fig. 4. As in Fig. 3, but with low-pass filtered yearly random noise added to represent the effect of interannual temperature variability.

In the correlation plot (Fig. 4c) we now see the -1 and +1 correlation are attenuated, and are more similar to the CMIP6 model-based correlations in Fig. 2. Note that there is little advantage in trying to match the spectral characteristics of interannual variations (noise) of the synthetic simulations to the CMIP6 models because with only 50 synthetic models just the variation in the noise seed produces considerable variations in the resulting correlation.

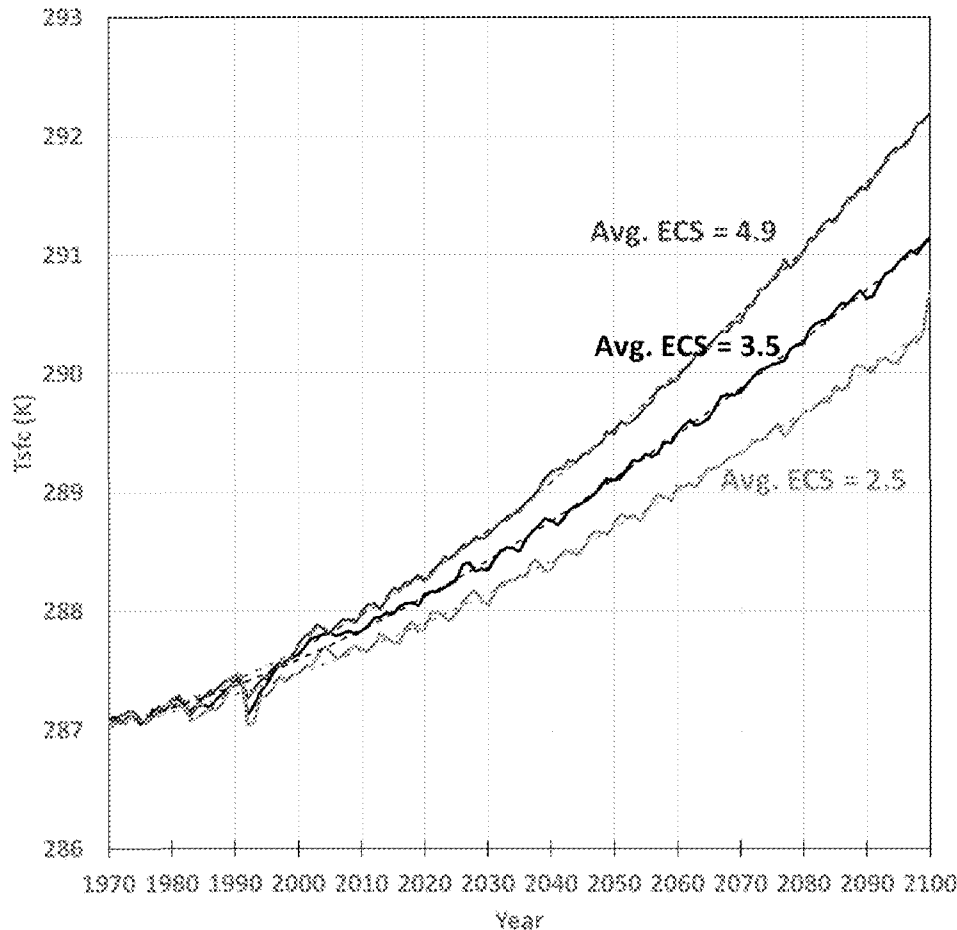
No matter the detail character of the prescribed synthetic interannual variability, and the specified strength of that variability, the basic result remains the same: when the baseline period used for anomaly computation has a non-zero temperature trend, negative correlations exist in the early years between temperature anomalies and long-term warming. This is not desirable behavior if one wants to see evidence of long-term warming as early in the record as possible. This is especially true when dealing with comparisons to observational datasets of limited record length, such as the satellite tropospheric temperature record since 1979 (ref).

d. Nonlinear warming with interannual variability

Since we are addressing the period of most rapid warming (and most rapidly increasing atmospheric CO₂ concentrations) beginning in the late 20th Century, a warming trend will exist in the first few decades, whether in climate models or in observations. That warming, however, has been somewhat nonlinear, with weaker warming during the 1970s and 1980s. This is likely due to aerosol negative radiative forcing being of comparable magnitude to the positive radiative forcing from increasing CO₂. After the 1980s, radiative forcing dominates and warming in the models typically accelerates.

If we average the 31 models in Fig. 1a into three groups with those nine models with the highest ECS, nine with the lowest ECS, and thirteen models in between those two extremes, we see the nonlinear character of the model warming in all three groups (Fig. 5).

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188 Fig. 5. CMIP6 model global average surface temperatures grouped into high, medium,
 189 and low ECS categories (solid lines), with 3rd order polynomial fits (dashed lines), and small
 190 vertical offsets applied so all time series align in 1970.

191 Note that these nonlinearities, with weak warming in the 1970s and 1980s, might be expected
 192 to impact our conclusions regarding the use of anomalies calculated relative to those early
 193 years since it weakens the warming trend in the first few decades. To address this possibility,
 194 we created synthetic temperature time series with nonlinear characteristics similar to those
 195 seen in the CMIP6 models. This was done by fitting 3rd order polynomials to each of the
 196 models' time series during 1970-2100, and using the average of those fit coefficients, as well
 197 as their standard deviations and the correlations between coefficients, to generate CMIP6-like
 198 time series. These are shown in Fig. 6.

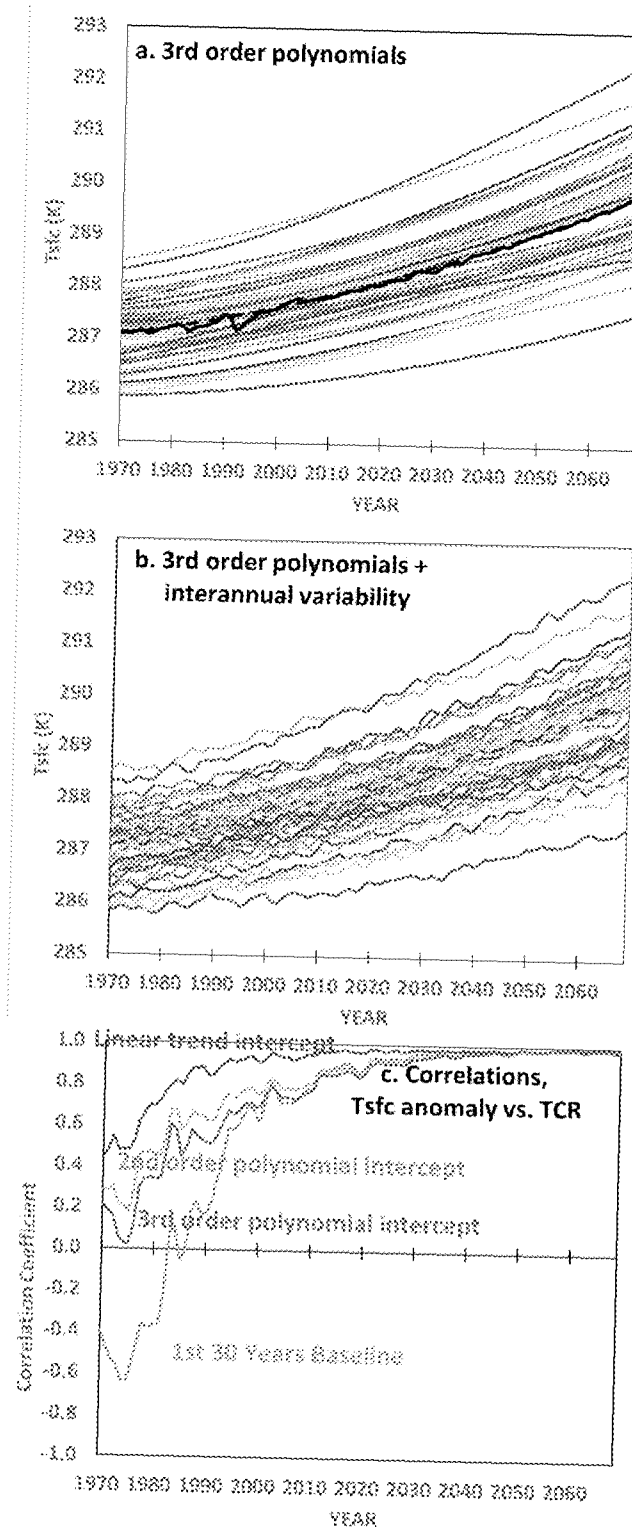


Fig. 6. (a) CMIP6-like synthetic nonlinear temperature time series, 1970-2070, using 3rd order polynomials; (b) those polynomials with noise-generated interannual variability added, and (c) the resulting yearly correlations between temperature anomalies and TCR (warming 1970-2100) for several methods of baseline removal to compute anomalies.

The results in Fig. 6c suggest that use of the linear trend y-intercept removed from each of the time series produces the best results in terms of a high correlation in the early years between the computed temperature anomalies and the synthetic models' net warming from 1970 to 2100.

That the correlations would be higher for the linear than the nonlinear fits to the time series was unexpected, and upon further investigation turns out to be the result of that nonlinearity.

Column 1 Heading	Column 2 Heading	Column 3 Heading
Entry 1,1	Entry 1, 2	Entry 1,3
Entry 2, 1	Entry 2, 2	Entry 2, 3

Table 1. This is an example table.

Acknowledgments.

Paste your acknowledgments here.

Data Availability Statement.

Paste your data availability statement here. For more information about data availability statements please see the [Data Policy and Guidance](#) page.

APPENDIX

Appendix Title

(Optional) Multiple appendixes should be indicated with a header Appendix A, Appendix B, etc., along with a descriptive title and at least a sentence or two of explanatory text. Appendix tables and figures should be embedded in the appendix section.

REFERENCES

A few of the most common reference types are shown below as examples. Each in-text citation must have a corresponding reference, and each reference listed must be cited in the text. References should be arranged alphabetically without numbering.

Example References:

Antonov, J. I., R. A. Locarnini, T. P. Boyer, A. V. Mishonov, and H. E. Garcia, 2006: Salinity. Vol. 2, *World Ocean Atlas 2005*, NOAA Atlas NESDIS 62, 182 pp.

Batchelor, G. K., 1981: *An Introduction to Fluid Dynamics*. Cambridge University Press, 615 pp.

Christensen, J. H., and Coauthors, 2007: Regional climate projections. *Climate Change 2007: The Physical Science Basis*, S. Solomon et al., Eds., Cambridge University Press, 847–940.

IPCC, 2013: *Climate Change 2013: The Physical Science Basis*. Cambridge University Press, 1535 pp., <https://doi.org/10.1017/CBO9781107415324>.

Kalnay, E., and Coauthors, 1996: The NCEP/NCAR 40-Year Reanalysis Project. *Bull. Amer. Meteor. Soc.*, **77**, 437–471, [https://doi.org/10.1175/1520-0477\(1996\)077<0437:TNYRP>2.0.CO;2](https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2).

Knutti, R., 2014: IPCC Working Group I AR5 snapshot: The rcp85 experiment. DKRZ World Data Center for Climate, accessed 14 October 2014, <https://doi.org/10.1594/WDCC/ETHR8>.

IPCC, 2021: *Climate Change 2021: The Physical Science Basis*. Chapter 3, Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Eyring, V., N.P. Gillett, K.M. Achuta Rao, R. Barimalala, M. Barreiro Parrillo, N. Bellouin, C. Cassou, P.J. Durack, Y. Kosaka, S. McGregor, S. Min, O. Morgenstern, and Y. Sun, 2021: Human Influence on the Climate System. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K.

259 Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University
260 Press, Cambridge, United Kingdom and New York, NY, USA, pp. 423–552, doi:
261 10.1017/9781009157896.005 .]

262

From: Park, Charles <charles.park@hq.doe.gov>
Sent: Monday, August 4, 2025 12:46 PM
To: curry.judith@gmail.com; Ross McKittrick; John Christy; Steven Koonin; Roy Spencer
Cc: Ison, Jeremy T.
Subject: Contact Information

Good afternoon:

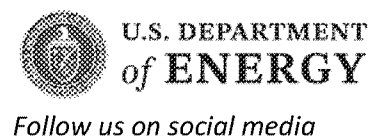
Thank you for your continued work on the report.

Moving forward, my colleague Jeremy Ison will be the point of contact.

Please direct all communications and inquiries to Jeremy Ison at jeremy.ison@hq.doe.gov.

Thank you,

Charles



Charles Park
*Deputy General Counsel –
Energy Policy*
Office of General Counsel
OFFICE 202.586.5281
MOBILE 240.220.0969

From: Judith Curry <curry.judith@gmail.com>
Sent: Tuesday, May 20, 2025 11:42 AM
To: Ross McKittrick; Roy Spencer; John Christy; Steven Koonin; Travis Fisher
Subject: correct version
Attachments: 9 Sea level.may8.docx

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9 Changes in Sea level

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of the volume of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (B. Fox-Kemper et al., 2021). The rate of global sea level rise is estimated to be 0.12 inches/year (for reference, 0.12 in is the height of two stacked pennies) (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

9.1 U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 9.1 shows that in Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show rises between 0.12 inches/year, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. That latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (G Wöppelmann and M Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (e.g. for urban development purposes) and subsurface extraction of groundwater, oil, or gas.

Table 9.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; C Letetrel et al., 2015; MA Karegar et al., 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative

sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

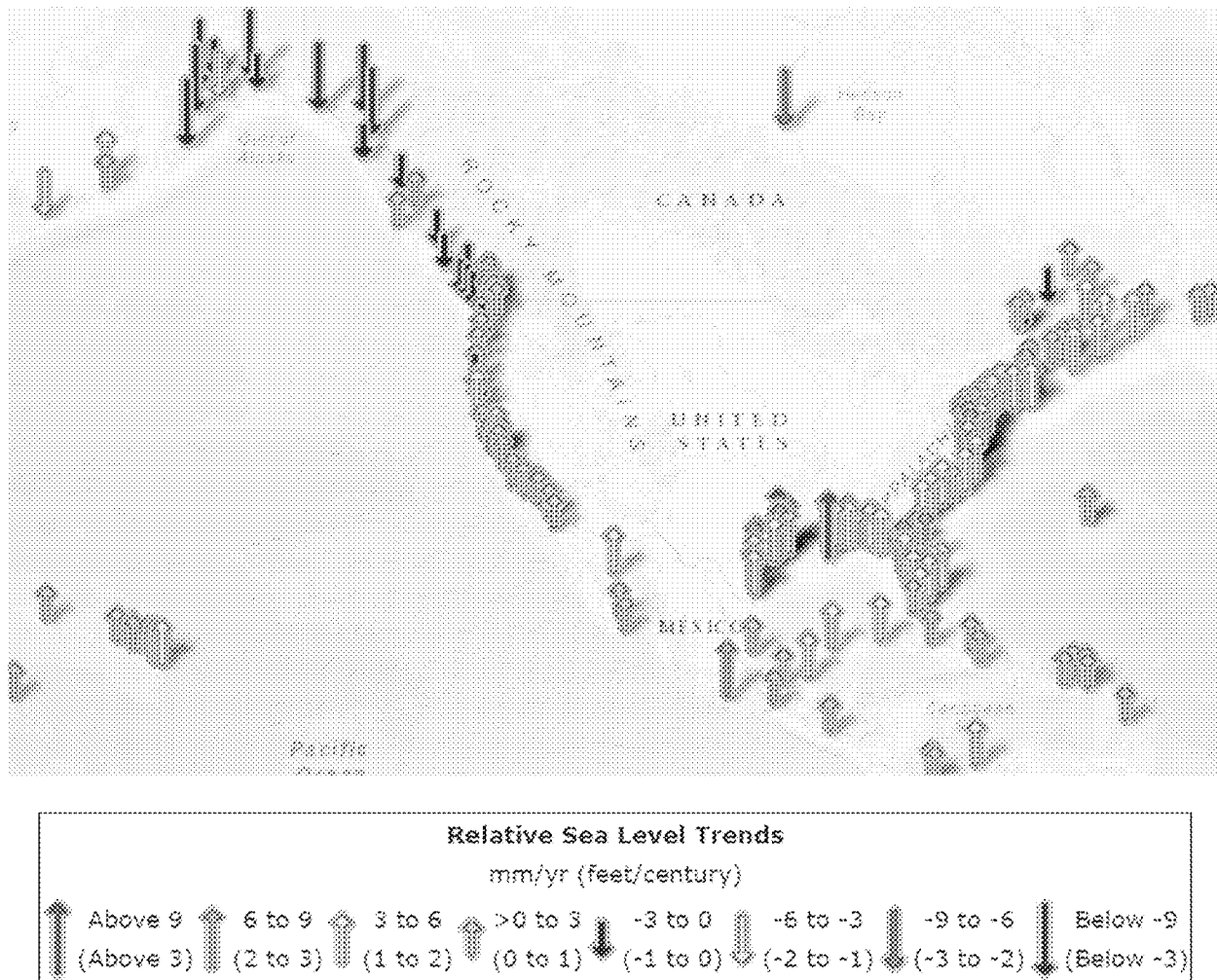


Figure 9.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Table 9.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 9.2). As shown in Table 9.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (M Shirzaei and R Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, have been caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

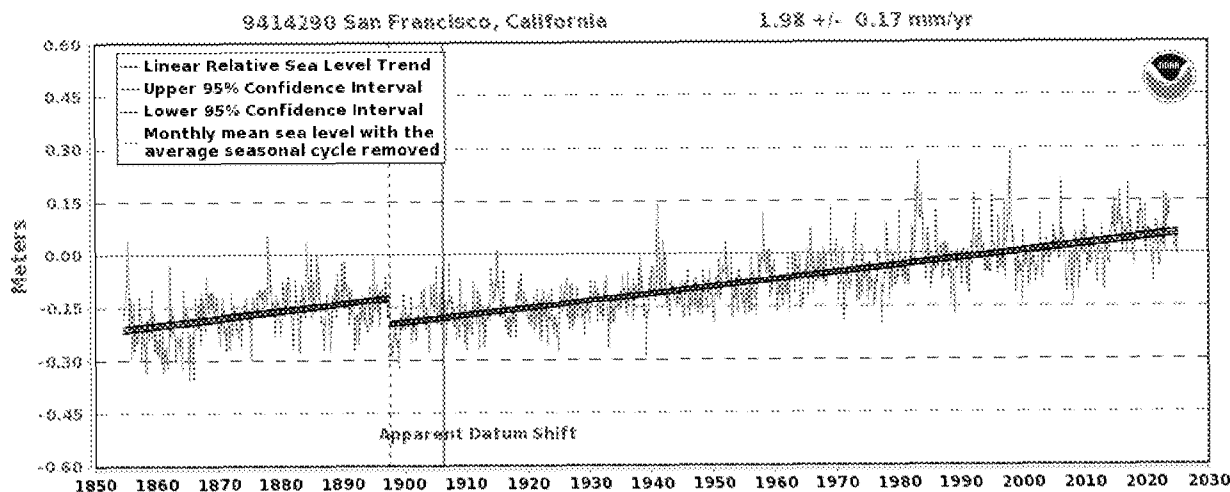


Figure 9.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 9.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 9.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (MC Kasmarek and JK Ramage), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes have been the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the deadliest U.S. natural disaster (JE Weems, 2016). Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula, literally removing significant portions of the land mass (UCS, 2017). While only 17 people were killed in Texas, property damage exceeded \$50 billion (A White, 2017). In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages (NOAA, 2025).

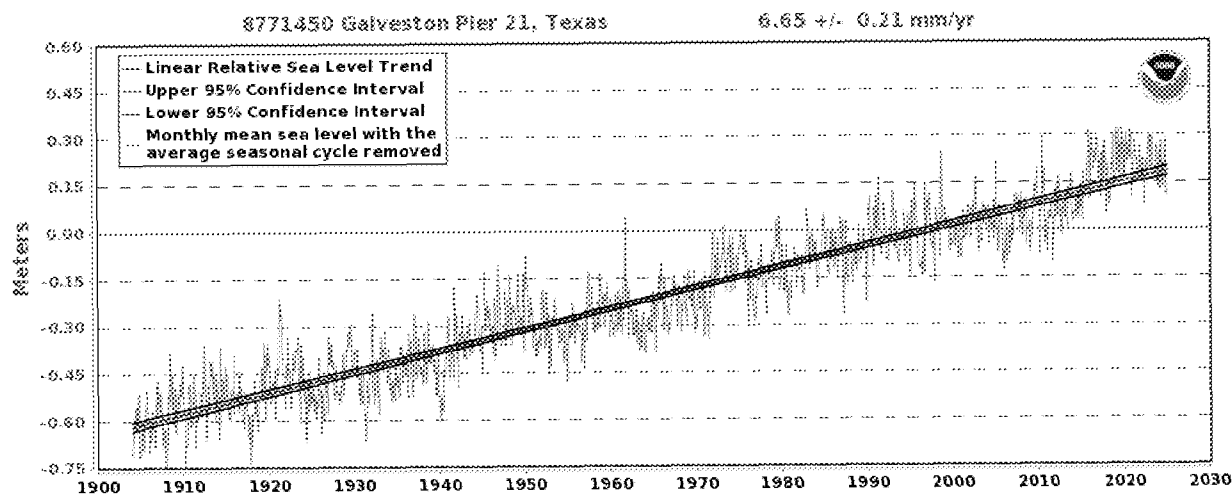


Figure 9.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 9.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 9.1 gives the absolute sea level rise as +0.08 inches/year.

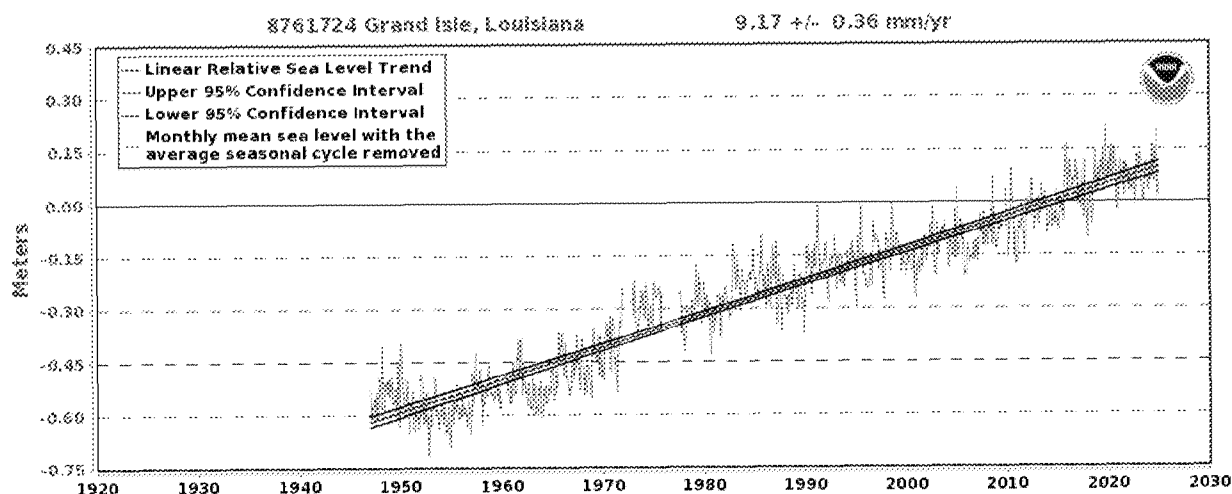


Figure 9.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi's suspended sediment load by ~50% (JM Malooney, 2018). A new subsidence map

of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (JH Neinhuis et al., 2017). As the city's elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans' problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (the Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 9.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55% of the measured relative sea level rise.

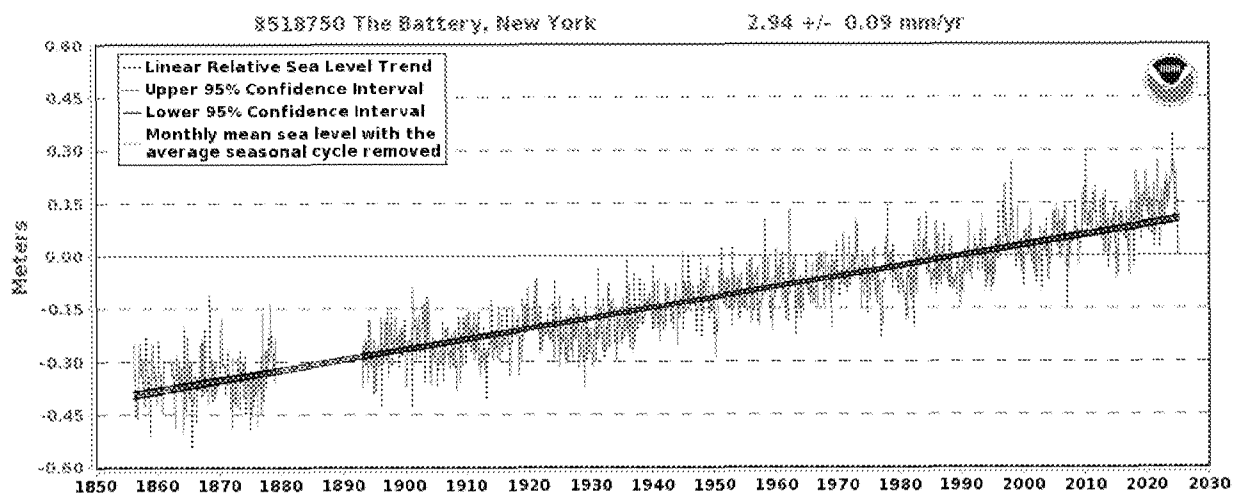


Figure 9.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Superstorm Sandy, New York developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York* (CNY, 2013). A broad range of coastal protection measures are outlined that match the risks facing the various zones: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

9.2 Projected sea level rise

The concern over sea level rise is not about the roughly 8 inches of global rise since 1900. Rather, it is about projections of rise century based upon simulations of a warming climate through the 21st Century.

The IPCC AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet

processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (B. Fox-Kemper et al., 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (B. Fox-Kemper et al., 2021). There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 9.2–9.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

9.3 Summary

Since 1900, global sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also with ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood hypothetical ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. From the tide gauge measurements in Figures 9.2–9.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

1. B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.
2. NASA, *NASA Sea Level Rise Portal: 2020 Edition* (NASA, 2020), <https://www.nasa.gov/specials/sea-level-rise-2020/>.
3. NOAA Center for Operational Oceanographic Products and Services (CO-OPS), *Sea Level Trends*, National Oceanic and Atmospheric Administration, accessed May 8, 2025, <https://tidesandcurrents.noaa.gov/sltrends/>.
4. Wöppelmann, G., and M. Marcos (2016), Vertical land motion as a key to understanding sea level change and variability, *Rev. Geophys.*, 54, 64–92.
5. NOAA Tides & Currents, Relative Sea Level Trends - <https://tidesandcurrents.noaa.gov/sltrends/>.
6. NAS (2012) *Sea-Level Rise for the Coasts of California, Oregon and Washington: Past, Present, and Future*. Appendix A: Vertical Land Motion and Sea-Level Data Along the West Coast of the United States. National Academies Press, NAP.edu/10766.
7. Camille Letetrel et al., “Estimation of Vertical Land Movement Rates along the Coasts of the Gulf of Mexico over the Past Decades,” *Continental Shelf Research* 111, Part A (December 1, 2015): 42–51, <https://doi.org/10.1016/j.csr.2015.10.018>.
8. Makan A. Karegar, Timothy H. Dixon, and Simon E. Engelhart, “Subsidence along the Atlantic Coast of North America: Insights from GPS and Late Holocene Relative Sea Level Data,” *Geophysical Research Letters* 43, no. 7 (April 2016): 3126–3133, <https://doi.org/10.1002/2016GL068015>.
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10. Mark C. Kasmarek and Jason K. Ramage, *Water-Level Altitudes 2017 and Water-Level Changes in the Chicot, Evangeline, and Jasper Aquifers and Compaction 1973–2016 in the Chicot and Evangeline Aquifers, Houston-Galveston Region, Texas*, U.S. Geological Survey Scientific Investigations Report 2017–5080 (Reston, VA: U.S. Geological Survey, 2017), <https://doi.org/10.3133/sir20175080>.
11. John Edward Weems, “Galveston Hurricane of 1900,” *Texas State Historical Association*, March 15, 2016, <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.
12. Union of Concerned Scientists, “Galveston County, Texas, Faces Sea Level Rise and Storms,” June 23, 2017, <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.
13. NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73.
14. Jillian M. Maloney et al., “Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation,” *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.
15. Jaap H. Nienhuis et al., “A New Subsidence Map for Coastal Louisiana,” *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.
16. City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.
17. B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change.”

From: Roy Spencer [roywspencer@hotmail.com]
Sent: 5/22/2025 11:04:40 AM
To: John Christy [climateman60@gmail.com]; Ross McKittrick [ross.mckittrick@gmail.com]; Judith Curry [curry.judith@gmail.com]; Steven Koonin [steven.koonin@gmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]
Subject: CORRECTED new Fig. 5.5 (note the 38-model average bar)
Attachments: paste.png

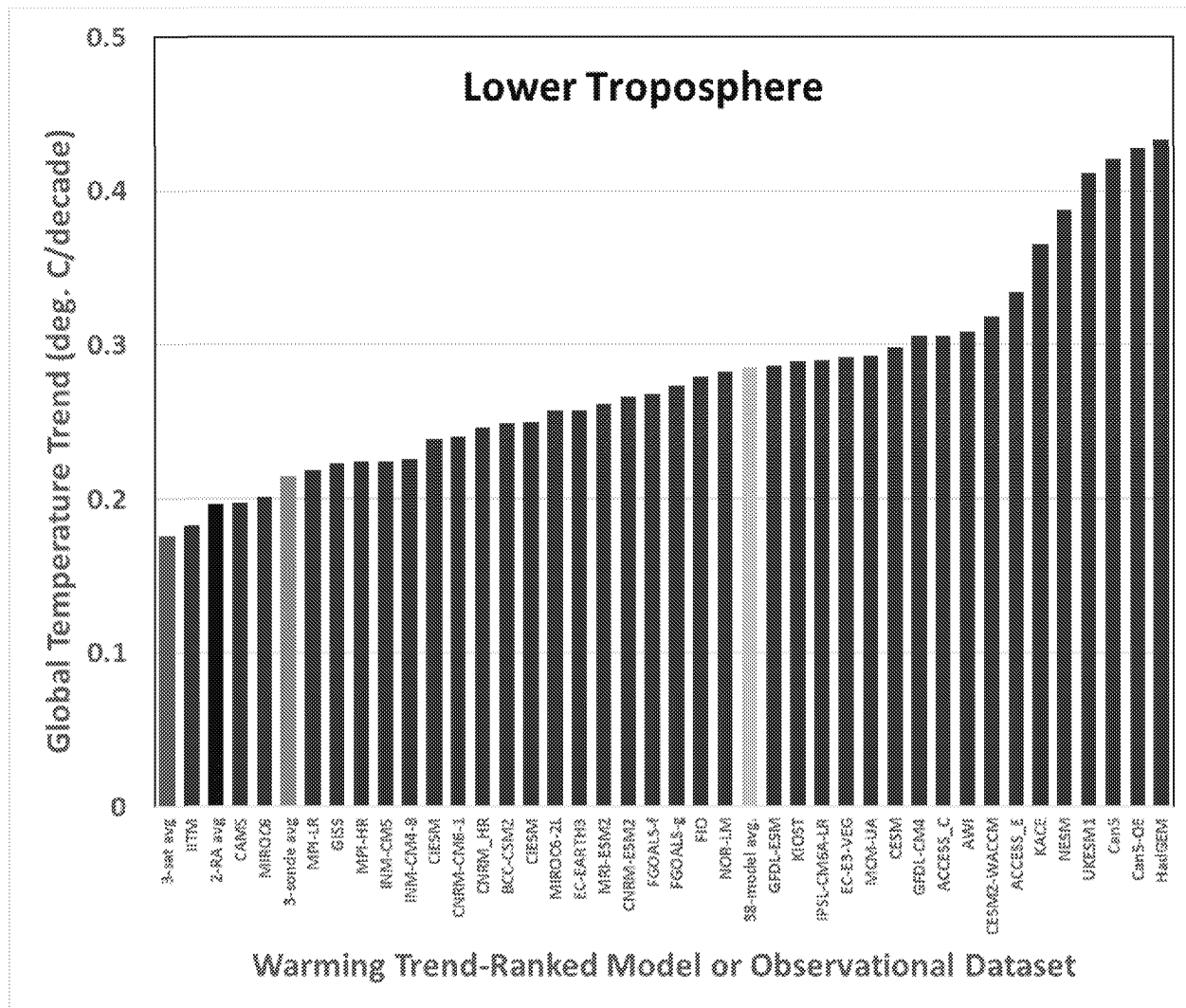
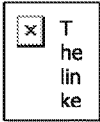


Fig. 5.5 Global lower-tropospheric temperature trends, 1979-2024, from various CMIP6 climate models (red, 38-model average in orange); the average of three satellite datasets (blue); the average of two reanalysis datasets (black); and the average of three radiosonde datasets (green).

From: Judith Curry [curry.judith@gmail.com]
Sent: 6/12/2025 3:57:52 PM
To: Ross McKittrick [ross.mckittrick@gmail.com]
CC: Steven Koonin [steven.koonin@gmail.com]; Roy W. Spencer [roywspencer@hotmail.com]; John Christy [climateman60@gmail.com]; Travis Fisher [travis.scott.fisher@gmail.com]; Josh Loucks [loucksj14@gmail.com]
Subject: curry bio sketch
Attachments: curry biosketch.docx

Attached is a beefed up version of my biosketch (previous one was relatively skimpy)

--



Judith Curry, President
CFAN - Climate Forecast Applications Network
Reno, NV USA
curry.judith@cfanclimate.com | +1.404.803.2012
<http://www.cfanclimate.net>

Judith Curry, Ph.D. is Professor Emerita at the Georgia Institute of Technology, where she served as Chair of Earth and Atmospheric Sciences for 13 years. She is President and co-founder of Climate Forecast Applications Network (CFAN). Curry has a PhD in Geophysical Sciences from the University of Chicago. She has authored or coauthored 192 peer-reviewed papers in atmospheric and climate sciences, two textbooks, and most recently the book *Climate Uncertainty and Risk*. Curry is a Fellow of the American Meteorological Society, the American Association for the Advancement of Science, American Geophysical Union, and a Member of the American Academy of Sciences and Letters. She has served on several Science Steering Committees of the World Climate Research Program and also the DOE Biological & Environmental Research Advisory Committee, Earth Science Subcommittee of the NASA Advisory Council, and the NRC Space Studies Board and Climate Research Committee. Dr. Curry has given testimony in 13 Congressional Hearings.

From: John Christy <climateman60@gmail.com>
Sent: Saturday, June 7, 2025 2:44 PM
To: Ross McKittrick; Steve Koonin; Judith Curry; Roy W. Spencer; Travis Fisher; Josh Loucks; seth.cohen@hq.doe.gov
Subject: CWG25 Errata
Attachments: CWG25_Errata_JRC_250607.docx; Untitled attachment 03419.htm; Fig_6.4.2_250607.png; Untitled attachment 03422.htm; Fig_6.4.3_250607.png; Untitled attachment 03425.htm; Fig_6.4.4_250607.png; Untitled attachment 03428.htm; Fig_6.4.5_250607.png; Untitled attachment 03431.htm

Ross

Since you held the Master for the CWG25 report to Wright, could you hold a folder of Errata that have been discovered? As I mentioned earlier, my precipitation categories included only one month in 2024 in the 2020-2024 bin rather than the whole year. Attached are the corrected charts and a document with small changes in some of the quantities on which they depend. Otherwise the text and conclusions are unaffected.

There will probably be more later, but back to the NCA5.

John C.

John Christy
Director, Earth System Science Center
Professor, Atmos and Earth Science
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7 June 2025

Errata to CWG 28May2025

John Christy

Replace Figs. 6.4.2 to 6.4.5. Published versions included only Jan 2024 data rather than Jan-Dec 2024 data.

Additionally, Fig. 6.4.4 was an early version using only 21 stations. The text describes results for 27 stations, so this corrected figure will have values about 6 units greater to account for the events determined for the 6 extra stations.

With additional data for 2024, the following values change.

Page 65

Was ... 72 percent of events ...

Now ... 77 percent of events ...

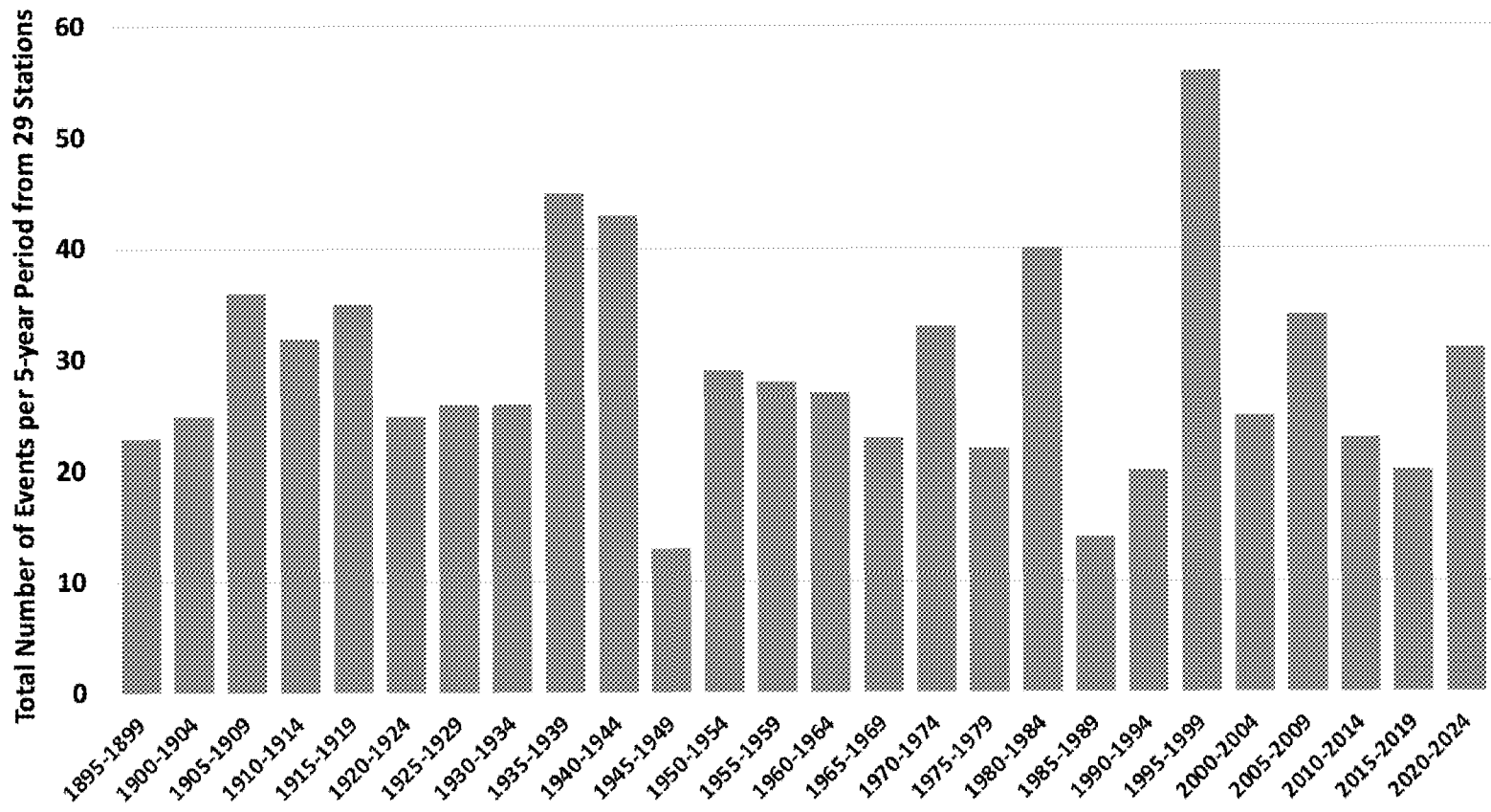
Was ... find a 51 percent increase ...

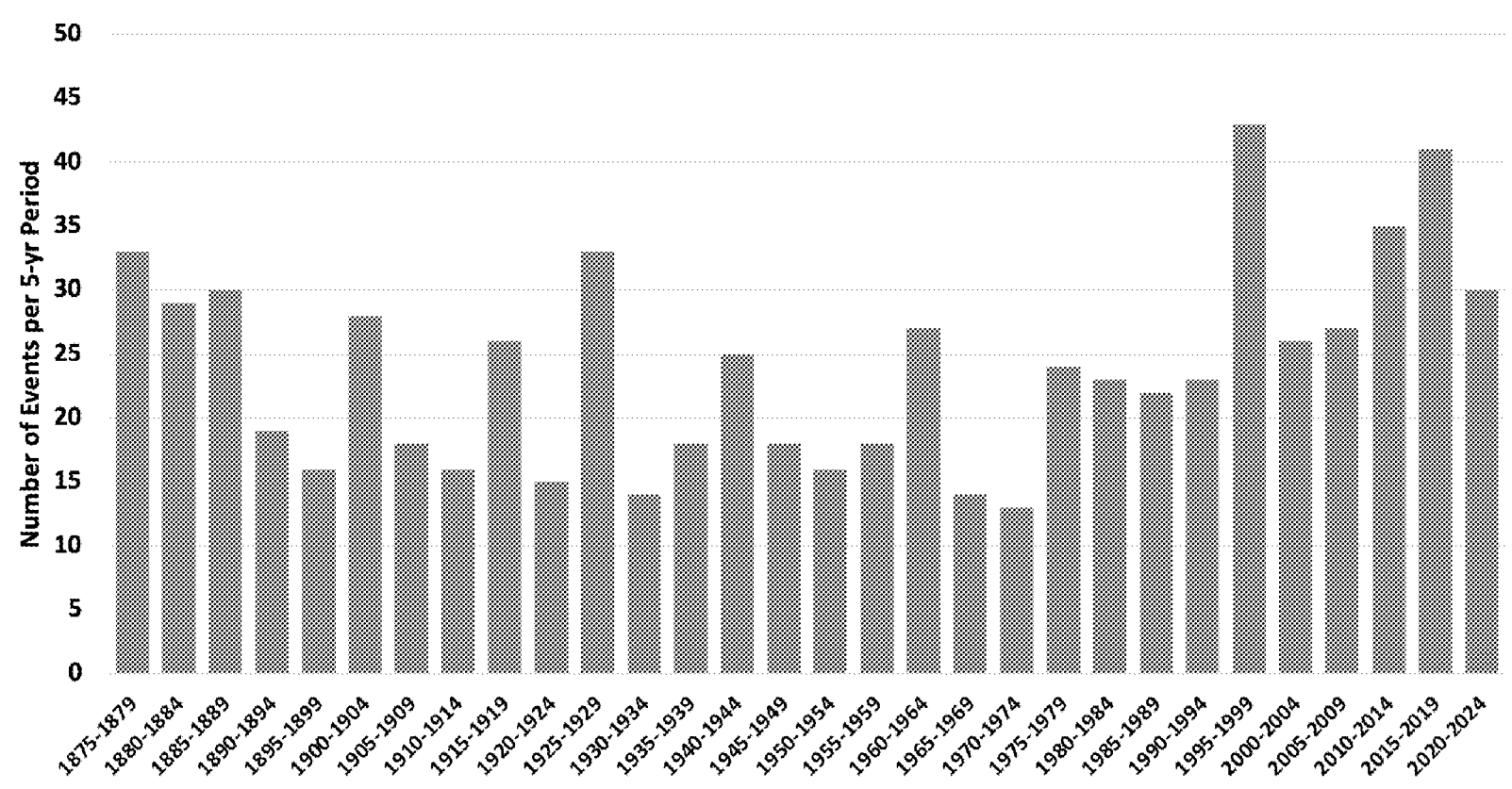
Now. ... find a 58 percent increase ...

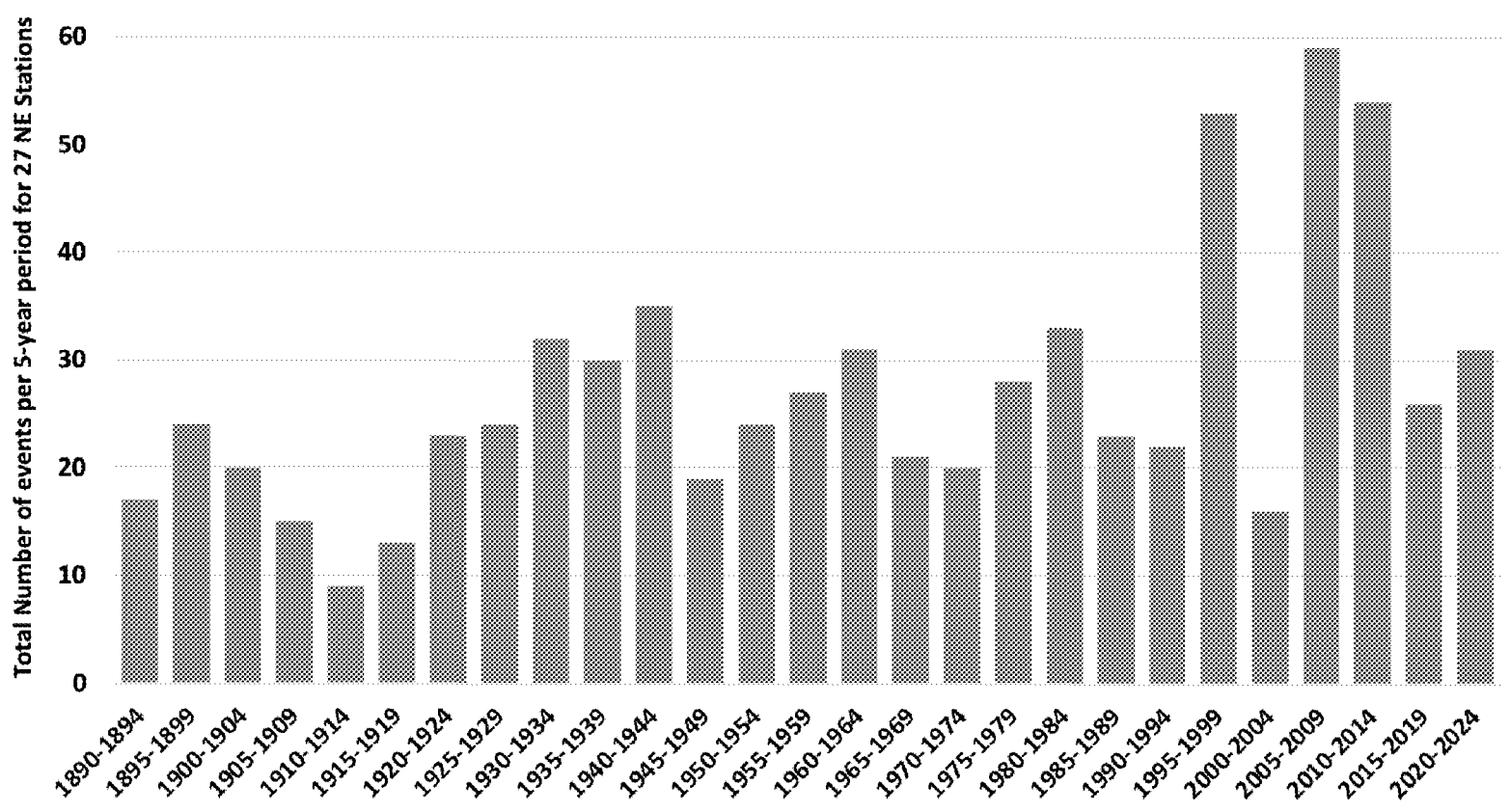
Page 66

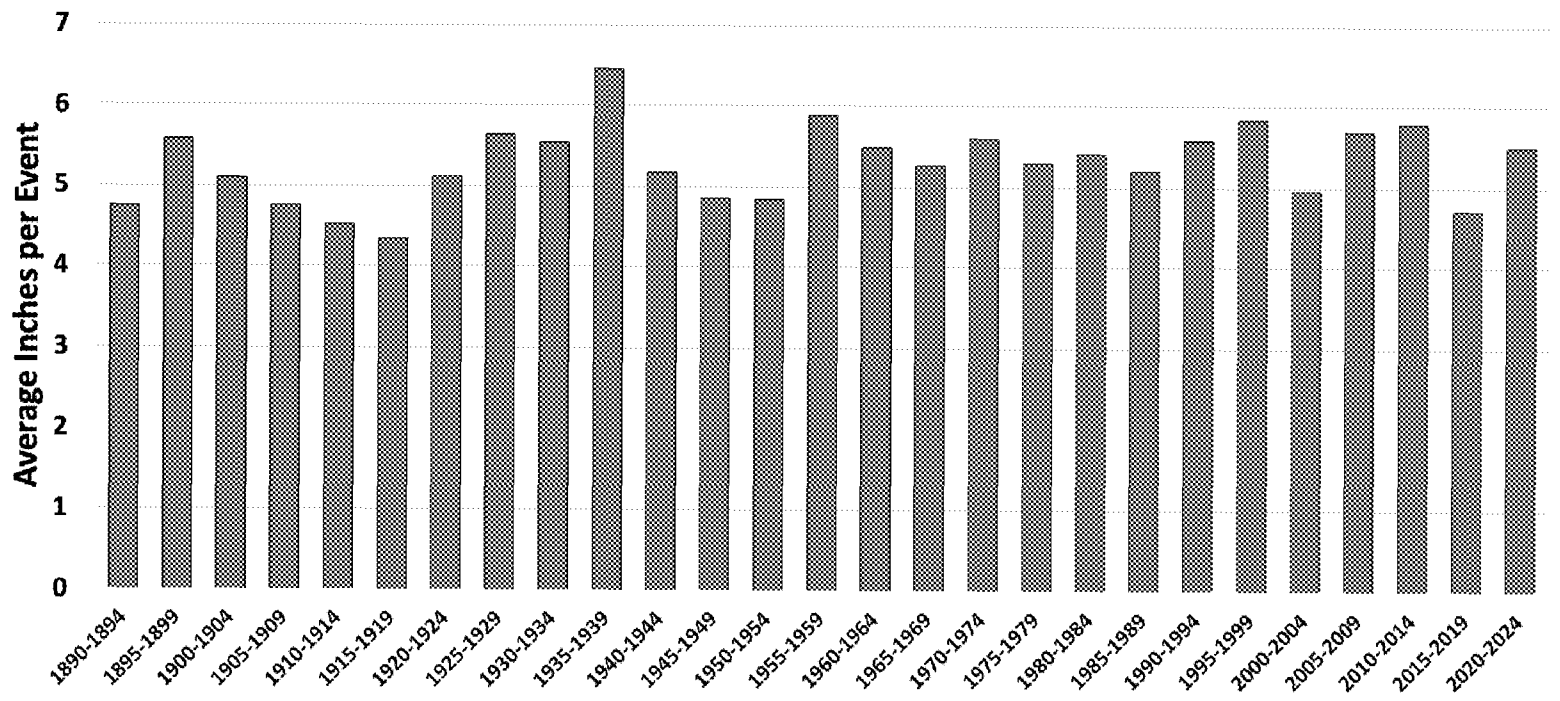
Was. ... only +0.02 inches/decade.

Now ... only +0.04 inches/decade.









From: Judith Curry <curry.judith@gmail.com>
Sent: Saturday, August 2, 2025 10:37 AM
To: Steven Koonin
Cc: Travis Fisher; Ross McKittrick; Roy Spencer; Charles Park; John Christy; Joshua Loucks; Seth Cohen; Audrey Barrios
Subject: DOE Internal Reviews
Attachments: DOE review responses.zip

Attached is a zip file of the edited DOE reviews. Probably good to have one more set of eyes look at this. Note: #1 and #6 required the most editing



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Pg	Para	Comment or Suggested Edit	
viii	2	The greening effect can't be due to increase in CO2 alone. The fertilization effect needs Nitrogen and phosphorous. There is observational[1] evidence that nitrogen available to plants is decreasing with increasing CO2 and thus acting to limit fertilization effect. Secondly, the greening of some portions of the planet are likely due to changes in precipitation patterns associated with changing climatic conditions and not entirely attributable to fertilization effect. We will also need to consider that the temperature effect on photosynthesis will also be a limiting mechanism to any continued greening due to fertilization in the future [2]. I recommend acknowledging that the greening is not attributable to CO2 alone and continued greening in the future with increasing CO2 is uncertain. Changed sentence to “Elevated concentrations of CO₂ directly enhance plant growth, globally contributing to “greening” the planet”	[1] Rachel E. Mason et al. Evidence, causes, and consequences of declining nitrogen availability in terrestrial ecosystems. Science 376, eabh3767(2022). DOI:10.1126/science.abh3767 [2] C.E. Moore, et al. The effect of increasing temperature on crop photosynthesis: from enzymes to ecosystems. Exp. Bot., 72 (8) (2021), pp. 2822-2844
viii	3	I am glad we acknowledge that CO2 causes warming, though I am not sure why we are not considering other energy sector related emissions that also cause warming (CFCs/HFCs, methane, aerosol effects). It is not clear what is meant by "CO2 emissions have tended to overestimate observed trends". This is not correct, the cumulative emissions track the RCP8.5 scenario the closest [3,4]. While there was a decrease in emissions during the Covid-19 period the emissions are now back on track following RCP8.5. This statement should clarify what is meant by the statement in the text. Rewrite sentence in the summary section to read “Climate change simulations require scenarios of distant future emissions. There is evidence that scenarios widely-used in the impacts literature have overstated observed and likely future emission trends.” On page 16 text added “Schwalm et al. (2020) defended the use of RCP8.5 on the grounds that cumulative CO2 emissions over 2005-2020 track it more closely than the lower RCP scenarios. They also argue that a modified version of the IEA scenarios closely track RCP8.5 in the coming decades. Hausfather and Peters (2020b) responded that the skill of RCP8.5 over those 15 years is due to offsetting errors in its representation of CO2 from fuel use and land use change, and the apparent agreement with IEA in coming decades is due to Schwalm et al. adding in very high land use emissions. The IEA’s own projected CO2 emissions track well below RCP8.5.”	[3] C.R. Schwalm, S. Glendon, & P.B. Duffy, RCP8.5 tracks cumulative CO2 emissions, Proc. Natl. Acad. Sci. U.S.A. 117 (33) 19656-19657, https://doi.org/10.1073/pnas.2007117117 (2020). [4] C.R. Schwalm, S. Glendon, & P.B. Duffy, Reply to Hausfather and Peters: RCP8.5 is neither problematic nor misleading, Proc. Natl. Acad. Sci. U.S.A. 117 (45) 27793-27794, https://doi.org/10.1073/pnas.2018008117 (2020).

viii	4	This paragraph seems to be talking about equilibrium climate sensitivity. The most recent model inter-comparison gives a wider range of climate sensitivities in the range of 1.8 to 5.7 and is wider than estimates of climate sensitivities that have been estimated from paleoclimatic and more recent historical datasets, in the range could be in the range of 2.3 to 4.5 K[5]. The higher sensitivity in the most recent model assessments are an area of active investigation by modelers, the feasibility of a higher range needs to be confirmed with additional observational and process scale modeling [6]. The range for climate sensitivities, 1.8-2.7, should be corrected to the most recent findings, 2.3-4.5. We should also recognize that the (a)earth is a complex system of systems (b)we can't do an experiment to find out what is correct or reduced the uncertainty. As we get better at extracting temperature records and CO2 concentrations from paelo data, there will be better reconstructions and possibly narrower range along with improvements in modeling that resolve many physical, biological and chemical processes as we get to higher and cloud resolving spatial resolutions. We discuss Sherwood et al. in Ch 4. Sentence changed: “Data-driven methods yield a lower and narrower range.”	[5] Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., et al. (2020). <u>An assessment of Earth's climate sensitivity using multiple lines of evidence</u>. <i>Reviews of Geophysics</i>, 58, e2019RG000678. https://doi.org/10.1029/2019RG000678 [6] Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). <u>Causes of higher climate sensitivity in CMIP6 models</u>. <i>Geophysical Research Letters</i>, 47, e2019GL085782. https://doi.org/10.1029/2019GL085782
viii	5	This is again not true for the majority of the models in the AR6. Figure 7.19 in the IPCC AR6 report shows that majority of the models exhibit a range within the observational range. The models running hot in the most recent decades are the ones with climate sensitivities grate than 5K, which are 3 out of a total of 40 and it should be noted that about the same number of models also are running cold' compared to observed[7] Paragraph has been rewritten: The world’s several dozen global climate models offer little guidance on how much the climate responds to elevated CO , with the average surface warming under a doubling of the CO concentration ranging from 1.8°C to 5.7°C [Section 4.2]. Data-driven methods yield a lower and narrower range [Section 4.3]. Global climate models generally run “hot” in their description of the climate of the past few decades– too much warming at the surface and too much amplification of warming in the lower- and mid- troposphere [Sections 5.2-5.4]. The combination of overly sensitive models and implausible extreme scenarios for future emissions yields exaggerated projections of future warming.	[7]Hausfather, Z., Drake, H. F., Abbott, T., & Schmidt, G. A. (2020). <u>Evaluating the performance of past climate model projections</u>. <i>Geophysical Research Letters</i>, 47, e2019GL085378. https://doi.org/10.1029/2019GL085378
viii	5,6,7	There is very little dispute that these are challenging issues for climate science. Many of the issues identified here related to compound effects (subsidence and se-level rise; wildfire and forest management) that requires further scientific investigation. Identifying further research avenues/focus areas will be helpful to firm up some of the challenges faced in using the climate projections as discussed in the paragraph 9. There is no disagreement here.	

viii	9	The focus on uncertainty is relevant and should be emphasized in future research. However, as a reasonable policy pathways, making decisions in the face of these uncertainties is critical. Most of the climate uncertainties that we have confidence at this time can be considered Level 2 and Level 3 uncertainties, approaches such as scenario analysis (and others) are suggested and followed for making hazard and risk estimates for future conditions. For deep uncertainty hazards (for example tornadoes etc.) that we don't have enough data or capability to model, developing methods for assessing the uncertainty and risk should be a focus of future research. There is no disagreement here. See Curry's book Climate Uncertainty and Risk.	
2	3	The reason CO2 was identified as a pollutant is the health consequences of increased temperature, flooding and other climate impacts and not because of any direct affect on health dur to exposure to atmospheric CO2[8]. There is no disagreement here.	[8] https://www.cdc.gov/climate-health/php/effects/index.html
3	1/C hap ter su m ma ry	The summary should note that CO2 fertilization effects are limited by the availability of other critical plant nutrients (Nitrogen, Phosphorous). The fertilization effect is also constrained by higher temperature effecting photosynthesis[9] Added sentence: Other contributing factors included warming and increased nitrogen.	[9] Xinyuan Wei et al 2025 Environ. Res. Lett. 20 064013
3	3	The attribution of greening to primarily CO2 fertilization is questionable as per recent research. Specifically, in the Northern high latitudes (where the greening is most prominent), increases in temperatures due to climate change has been shown to provide the best explanation[10]. In the sub-Saharan region reforestation efforts and changing precipitation patterns lead to some of the observed greening (the great green wall) [11]. The attribution to CO2 fertilization should be qualified by noting the other present and emerging constraints. We cite Zhu et al attributing 70% of change to CO2 . That implies other factors matter as well.	[10]Liu, J., Wennberg, P.O. An emergent constraint on the thermal sensitivity of photosynthesis and greenness in the high latitude northern forests. Sci Rep 14, 6189 (2024). https://doi.org/10.1038/s41598-024-56362-1 [11] Francesco S.R. Pausata, Marco Gaetani, Gabriele Missouri, Alexis Berg, Danielle Maia de Souza, Rowan F. Sage, Peter B. deMenocal, The Greening of the Sahara: Past Changes and Future Implications, One Earth, Volume 2, Issue 3, 2020, Pages 235-250, ISSN 2590-3322, https://doi.org/10.1016/j.oneear.2020.03.002 .
3	5	This summarization ignores the compound effects of temperature, moisture and CO2 fertilization in assessing the impacts of CO2 increase on vegetation and crop yields. Many studies have shown that [12]. Making note of these compensating factors is required for a balanced view on CO2 fertilization effects on plants. This issue is addressed in Chapter 9	[12]Lesk, C., Anderson, W., Rigden, A. et al. Compound heat and moisture extreme impacts on global crop yields under climate change. Nat Rev Earth Environ 3, 872–889 (2022). https://doi.org/10.1038/s43017-022-00368-8

4	1	Chen et al. (2024)[13] conclude that "In the attribution analysis of LAI trend and growth rate trend, there were some differences between multiple linear regression model and partial correlation analysis at high latitudes in the northern hemisphere. Partial correlation analysis showed that LAI trend and growth rate trend in this region were mainly affected by temperature and radiation, while multiple linear regression suggested that CO2 was the dominant driver. The results of the partial correlation analysis seem more reasonable because some previous studies have shown that vegetation change in the high latitudes of the northern Hemisphere is mainly positively affected by climate warming. Multiple linear regression model performed relatively poorly in this region and might not fully identify the contribution of individual drivers. In addition, our model does not include the contribution of land management, which has been highlighted in some previous studies. Of course, the contribution of land management to LAI trend and growth rate trend may be implied in other drivers, such as the positive contribution of CO2 to LAI trend in PP and PN areas". We have added the Chen references. Our existing summary doesn't conflict with this. They conclude CO2 is the dominant driver globally but not the only driver.	[13]Xin Chen, Tiexi Chen, Bin He, Shuci Liu, Shengjie Zhou, Tingting Shi, The global greening continues despite increased drought stress since 2000, Global Ecology and Conservation, Volume 49, 2024, e02791,ISSN 2351-9894,
6	1	This again suffers from not acknowledging the effects of compound and often compensating phenomena that is occurring with the on-going climate change. For example [14] note that much of the Midwest any benefit from CO2 fertilization will be negated by temperature increases. [15] note that "Our results show that long-term physiological acclimation dampens the initial stimulation of plant net carbon assimilation to elevated [CO2], and of plant water use to warming." The topic of agricultural productivity is addressed in Chapter 9 It is not disputed that effects of dT go negative at high enough levels. The 2013 paper by Ruiz-Vera et al doesn't provide much general information beyond the FACE experiment site. The C14 data set I used is a global sample and takes both dT and dC into account.	[14]Ursula M. Ruiz-Vera, Matthew Siebers, Sharon B. Gray, David W. Drag, David M. Rosenthal, Bruce A. Kimball, Donald R. Ort, Carl J. Bernacchi, Global Warming Can Negate the Expected CO2 Stimulation in Photosynthesis and Productivity for Soybean Grown in the Midwestern United States , Plant Physiology, Volume 162, Issue 1, May 2013, Pages 410–423, https://doi.org/10.1104/pp.112.211938 [15] Lamba S, Hall M, Rantfors M, et al. Physiological acclimation dampens initial effects of elevated temperature and atmospheric CO2 concentration in mature boreal Norway spruce. Plant Cell Environ. 2018; 41: 300–313. https://doi.org/10.1111/pce.13079
8	1	The fallacy of these arguments in terms of PH changes and evolution is that the changes described in this paragraph occurred over millennia and the evolutionary process had time to adapt; here with climate change we are talking about changes in our lifetime, the speed of change is the issue. This will lead to collapse of some ecosystem and by the time adaptation takes place it will be millions of years and in a different climate - not the one we have now and that enabled the rise of humans. The chapter notes large regional and even diurnal variations in ocean pH. We already address the issue of short timescale variations on p. 8: "On the time scale of thousands of years, boron isotope proxy measurements show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae <i>et al.</i>, 2018). Thus, ocean biota appear to be resilient to natural long-term changes in ocean pH since marine organisms were exposed to wide ranges in pH."	
5	Fig 2.2	A simple calculation will show us how misleading this figure is. It shows that over 600 Million years CO2 changed by around 6000ppm. That is a rate of change of 0.00001/yr; COE changed from 275 to 430 in the past 175 years, that is rate of change of 0.88ppm/yr. A change in the rate of over 10^5 in magnitude - there in lies the problem. We are seeing a rapid increase in CO2 that has never been witnessed and the ecosystem and huma society (which is at best 10K years old), may not be able to adapt to this rapid change. This figure has been deleted. We don't know what the rate of changes was on an annual or centennial time scale since the data are too low resolution. We have added the following sentence	

		“While the modern rate of change in CO2 is likely high compared to prior intervals, the geological evidence is that plants and animals evolved under much higher CO2 levels than at present.”	
12	Summary	The misuse of RCP8.5 as business as usual is acknowledged. However, this was never intended to be a no-policy or business as usual scenario but as a high-end baseline scenario. When dealing with interaction of physical systems with socio-economic projections (which tend to be highly uncertain and policy dependent), the development of this high baseline scenarios is intended to explore the uncertainty ranges that represent a high-end scenario[16,17]. As any engineer would acknowledge, this is a prudent approach when dealing with L3 and L4 type deep uncertainties and provide valid envelopes for assessing uncertainties and risks from high impact events/hazards. The rest of the statements here are uncertainties acknowledged by the climate scientists and included in developing projections and discussing the results[4]. Does the IPCC downplay the role of sun in climate change? The IPCC includes sun variability in all its assessments from the beginning and has been acknowledged as a potential but insignificant contributor. The comments do not imply any disagreement with what we have written. Extreme scenarios for models are useful for bracketing outcomes but our criticism (based on the literature) is the widespread use of RCP as a no-policy baseline; the reviewer acknowledges that was never its purpose. The IPCC’s assessment insignificance of the sun in climate change is based in part on use of low variability irradiance reconstructions that rule out it having any role. This is addressed in Chapter 8	[16]van Vuuren, D.P., Edmonds, J., Kainuma, M. et al. The representative concentration pathways: an overview. Climatic Change 109, 5 (2011). https://doi.org/10.1007/s10584-011-0148-z [17]Hausfather, Z. (2025). An assessment of current policy scenarios over the 21st century and the reduced plausibility of high-emissions pathways. Dialogues on Climate Change, 2(1), 26-32. https://doi.org/10.1177/29768659241304854 (Original work published 2025)
16	2,3, 4,5	Please see above. The business-as-usual may be a misnomer but this is an 95% case that is typically included in any type of prudent uncertainty analysis, in particular given the difficulty of predicting the evolution of socio-economic and political conditions over the next 100 years. It should be noted the difference between RCP8.5 and RCP4.5 for mid-century conditions that is of particular focus for adaptation studies in not significant and most of the divergence in these two scenarios occurs later in the century. Implausibility is not equivalent to very unlikely (e.g. 95th percentile), but rather includes impossible or implausible assumptions. High impact hazards occur independent of atmospheric CO2 concentrations (Chapter 6).	

19	5	That the dynamic vegetation models need more development is acknowledged and is a defining challenge for Earth System Modeling for the next decade. There is no disagreement here	
22	3	As noted, Parker[18,19,20] has investigated the Urban effects on temperature records. The finding establish that by comparing warm and wind conditions world wide that the impact is negligible. However, as noted by authors, this literature hasn't progressed much over the last decade and much more attention needs to be paid to this question by employing newer models, datasets and analytical techniques available to us at present. The CWG Report addresses this concern. We agree with the reviewer that the literature stalled a decade+ ago.	[18] Parker, D. Large-scale warming is not urban. Nature 432, 290 (2004). https://doi.org/10.1038/432290a [19]Parker, D.E. (2010), Urban heat island effects on estimates of observed climate change. WIREs Clim Change, 1: 123-133. https://doi.org/10.1002/wcc.21. [20]Parker, D. E., 2006: A Demonstration That Large-Scale Warming Is Not Urban. J. Climate, 19, 2882–2895, https://doi.org/10.1175/JCLI3730.1.
28	2	We can all agree that there is a desperate need for developing higher-resolution climate models that can get to cloud resolving scale so that we can represent the cloud feedbacks correctly in the model and avoid uncertainties from parameterization and scale dependency of the parameters. This doesn't make these models useless. The models provide directions for further improvements and necessary changes to reduce the uncertainty bands over the ECS. The climate models are useful for research purposes. The CWG Report demonstrates that they are not fit for the purpose of policy making. There's no guarantee increased resolution will be the answer, but if ever a model appears that can deal correctly with clouds that will be quite something. .	

29	2	The databased approaches have mostly been robust with changes at the high end around 3-4C and at the low end around 1.8 to 2.5C as noted in the chapter. It will be challenging to make this range shorter given the data requirements and uncertainties in data over paleo/haloacene periods. It seems reasonable to estimate that we may have ECS in the range of 3 to 4K (higher than 3.5K being less likely [21]) at the higher end and this should not prevent us from planning and thinking on ways to prevent this possible scenario as it could have major consequences for humans across the planet. The Report acknowledges that 4C is a reasonable upper bound for the likely range	[21] Michael Mann, Our Fragile Moment: How lessons from Earth's past can help us survive climate crisis, Hachette Group Inc., 2024.
32	3	The models range over a factor of three in ECS comparing the most sensitive to the least sensitive models. However vast majority of the models are in 3 to 3.5K sensitivity range and it is probably not correct to assign all models the same amount of importance, given the fact that some of institutes participating in the exercise have different levels of capacity to develop and test models. Only 5 of the models are between 3 and 3.5C Some of the most reputable models have the highest values of ECS, including UK and US models The point made in this paragraph is that research over several decades has not reduced the range of model ECS. For observers who rely on model outputs this is very concerning and again goes to the question of fitness for purpose, as posed in the prior paragraph.	
34	1	While this analysis for the CMIP6 model set is accurate and focuses on a dataset that has shown higher ECS than previous iterations. it should be noted the models have exhibited considerable skill in predicting the subsequent GMST warming[22]. The criticism of the CMIP6 based high ECS models may be premature and probably will have to wait additional time before passing judgement. As noted in [22] these models have shown considerable skill when evaluated on their projections over the past 30-40 years after the projections were published. Figure 5.3 in the Report clearly refutes this assertion Hausfather et al. did examine early model-obs matches but only using models that had relatively low ECS. The Scaffeta analysis covered a longer interval (1980-2021) than the Hausfather et al. analysis of SAR (1995-2017) and TAR (2001-2017). Its findings line up with Fig 5.3 and the tropospheric evidence in Fig 5.4.	[22]Hausfather, Z., Drake, H. F., Abbott, T., & Schmidt, G. A. (2020). Evaluating the performance of past climate model projections. Geophysical Research Letters, 47, e2019GL085378. https://doi.org/10.1029/2019GL085378
36	1	A recent study attributes the bias to inter-annual availability and residual bias in the satellite record. The pre- and post 2000 have temperature records from two separate satellites and the discrepancy in the trends needs to be resolved[23] Chung et al. (using output through 2014 only) confirm the models' too-high warming rates and suggested two issues that might contribute to at least part of the discrepancy: (1) the differential phasing of natural, ephemeral events such as El Niños between models and observations and (2) a possible spurious cooling in UAH and NOAA/STAR satellite datasets around 2000. Regarding (1) we agree that the timing of major events like ENSOs diminishes the fidelity of models-to-observations comparisons for short periods, but now with 46 years of record as well as two major El Niño warm events since 2014 in the observations, the results shown in Fig. 5.7 are quite appropriate for comparison. Regarding (2) Christy et al. 2018 (and later Zou et al 2023) specifically examined the divergence around 2000 between UAH and NOAA/STAR vs. RSS and UW demonstrating that RSS and UW's use of the aging and drifting NOAA-14 satellite relative to the new, highly calibrated NOAA-15 sensor contributed to a spurious warming in RSS and UW. Be that as it may, CWG Fig. 5.7 is clear in noting all models overestimate the tropical temperature trend relative to observations – model trends being even more positive than those of RSS and the two Reanlayses (in addition to UAH and NOAA/STAR).	[23]Chung, ES., Kim, SJ., Sohn, BJ. et al. Multi-decadal climate variability and satellite biases have amplified model-observation discrepancies in tropical troposphere warming estimates. Commun Earth Environ 5, 342 (2024). https://doi.org/10.1038/s43247-024-01510-8

38	3	This is challenge we need to face and work on improving the parametrizations. The new era of super high resolution models would resolve the complex interactions of turbulence, transport and clouds and will provide less uncertainty[24]. However, this can't be used to invalidate the entire set of models, the models are performing remarkably well given the complex system that is being modeled. It should be noted the models do cover the range of the observations and it is not outside the envelope of model predictions. The Report does not address invalidating the entire set of models. Rather we address the fitness-for-purpose of the models for policy making Fig 5.6 shows that to the extent there is a match with observations, it comes from models with very little CO2 response. “However, this can't be used to invalidate the entire set of models, the models are performing remarkably well given the complex system that is being modeled.” This statement is not supported by the evidence unless and until “remarkably well” is metricized for us to examine and make a determination. The paper cited doesn’t exactly apply to the real world (looking at Fig 1 doesn’t give one much confidence in models), but does give insight into the various models as best I can tell.	[24]Merlis, T. M., Guendelman, I., Cheng, K.-Y., Harris, L., Chen, Y.-T., Bretherton, C. S., et al. (2024). The vertical structure of tropical temperature change in global storm-resolving model simulations of climate change. Geophysical Research Letters, 51, e2024GL111549. https://doi.org/10.1029/2024GL111549
40	4	Part of the problem here may be which part of the stratosphere is sampled and the importance of interannual a variabilities in the lower part of the stratosphere. [25] have shown that including the stratosphere as defined from 25 to 50km there is high confidence that the cooling signal caused by CO2 increase is detectable and beyond the noise levels of the natural and inter annual variability in the lowest part of the stratosphere. We should put this debate to rest. Santer et al. (2023 has been added to the references with this text: Santer et al. (2023) use updated data to show that a cooling trend has not re-emerged in the lower stratosphere.	[25] B.D. Santer, S. Po-Chedley, L. Zhao, C. Zou, Q. Fu, S. Solomon, D.W.J. Thompson, C. Mears, & K.E. Taylor, Exceptional stratospheric contribution to human fingerprints on atmospheric temperature, Proc. Natl. Acad. Sci. U.S.A. 120 (20) e2300758120, https://doi.org/10.1073/pnas.2300758120 (2023).
42	2	Given the large uncertainties in obtaining data over much of the Northern Hemisphere, using a smaller regional analysis to discount the models may be inappropriate. We should that this remains a question we need to resolve developing better datasets with more seasonal and sub-seasonal coverage to test the model on a global scale The reviewer’s points are fine but it is important in the context of this report to point out discrepancies in the way models on some key continental-scale metrics such as, in this case, snow cover. This section directly addresses a region that is important to estimates of the Social Cost of Carbon in the context of agricultural productivity, again reiterating that the models are not fit for the purpose of policy making.	

44	3	This statement from [26] refers to the fitness of global scale models to resolve regional scale features and argues for developing model at higher spatial resolutions. Using downscaling and other techniques additional insights can be gained at regional scales and provide information for a set of 'purposes'. However, we should work on getting to regional and local scales with GCM as quickly as possible. The current model structural forms may not be adequate for resolving all of these issues merely by increasing spatial resolution. Simulating change at regional to local scales depends on getting the internal variability of the ocean correct, which is only partly a resolution issue.	
47	2	Looking for trends or estimating trends in extreme events in current and future climate is not necessarily an attribution study. Estimating frequency, duration and intensity of events helps understand the changing range of the hazard (if there is one). An attribution would be to find to what extent a particular event is influenced or affected by increase in CO2. I would consider these two not to be the same. We explain the distinction between detection and attribution	
47	3	Attributing any single event to changing climate is perilous, agreed. Yes. .	
47	5	As noted by [26] there is not yet any strong evidence that LPT is a fact We have eliminated mention of LPT explicitly, but retain elements of the text surrounding long term variability.	[26]Cohn, T. A., and H. F. Lins (2005), Nature's style: Naturally trendy, Geophysics. Res. Lett., 32, L23402, doi:10.1029/2005GL024476.
57	2	I am not sure how one can conclude that the temperature extremes have decreased based on figure 6.3.4. If I understand correctly the Tmax-Tmin for each year was tabulated and a mean of this difference averaged over the 100+ years was subtracted from these values to get some thing like a anomaly. This anomaly seems to have moved from +3F to -3F over the course of q00 years and now trending upwards again. This suggests to me that there has been significant changes in the extremes over the years and the most recent trend is towards warmer highs? For each station and each year, the hottest day and coldest night are determined and their difference computed. These differences are then geographically averaged for the CONUS and then an overall average is removed to show the results as a type of anomaly. Reviewer 1 is correct, as indicated in the text, Tmin temperatures are almost universally rising more rapidly than Tmax, hence, the difference (or range) has declined overall. A check of CMIP6 models for the CONUS under ssp4.5 shows half with TMax rising faster than TMin and (obviously) half vice versa – so there is no clear signal from models that matches the observations. The flattening (or slight rise in the metric) in the past 20 years is clearly within the natural range, but does reveal an interesting stair-step pattern with rapid declines centered around the 1940's and 1990's and relatively flat periods in between. An explanation is under investigation, and a leading hypothesis is that there was rapid growth of manufactured surfaces around weather stations in the 1940s.	

		Then, in the 1960s-80s many stations were re-located to relatively rural airports, which then experienced subsequent growth in manufactured surfaces around their weather stations in the 1990s. Thus, rapid nighttime warming in the 1940s and 1990s.	
58	3	The NCA5 is suggesting that the western US is experiencing increase in extreme heat (page 57, para 4); it seems like figure 6.3.5 establishes the fact and not contradict. There was no claim of pervasive (all CONUS) increase in the report We have deleted the sentence “The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.”Not worth going into more detail in this report	
59	4	The definition of heat wave as consecutive 6 days seems to be a special case. The standard definition is exceedance of 85 or 90 percentile for 2 or more days. I can't check with NCA5 as it was taken down from the web As correctly suggested by Reviewer 1, there are numerous ways to define a heat wave. CWG chose to follow one definition discussed in NCA4 (pg 191) and use 6 consecutive days with Tmax > 90th percentile so as to allow for consistent comparisons. However, changing the parameters will do little to alter the fundamental result that the 1920's to early 1950's contain the major heat wave events for the CONUS.	
60	1,2	Figure 6.3.6 establishes that heatwaves as defined here have increased in the west and have shown increasing trend all over CONUS in the past 50 years. [27] shows the results for the last 60 years and there is little doubt that there is an increase over most of the CONUS, again the NCA5 report is off the web; figure 6.3.7 shows the heat waves are monotonically increasing from the 1960. Including the longer data is only interesting in the dust bowl 1930 camouflage the signal somewhat for the Midwest and central plains. The problem of taking averages over large regions (for example entire CONUS) is that it kills the peak signals and smooths out the emergent climate change indicators. Doing continental averages to look for extremes is really not very useful. Secondly, there is no particular reason to assume that the climate change signal (i.e. the number of heat waves) should showing up 100 years ago, as the CO2 in the atmosphere started to be of significance in the last 50 years. As discussed in the CWG text, the EPA chart is (1) based on nighttime temperatures in the 50 largest US cities and (2) begins in 1961 which was the start of the coolest decade in over 100 years, thereby preconditioning the chart to have an upward trend. Urbanization is most clearly seen in nighttime temperature increases so this does not represent a change in the background climate, but more likely the local climates of cities. Rural areas show less nighttime warming. And, avoiding earlier warm periods does not provide information on the larger scale of natural variability. We have added a sentence at the end of Section 6.3 “Irrespective of the ultimate cause of regional trends, heatwaves have important effects on society which must be addressed, as we discuss in Chapter 10.”	[27] https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves

61	4	averaged over all stations in the region, none of these trend parameters is statistically significant'. This is again how one would be looking at statistics of extremes in precipitation. As we know, precipitation is highly heterogenous and location dependent. As observed there are trends even with the approaches chosen by the authors of this study compared to NCA5 and averaging that over and saying there is no trend seems disingenuous. We summarize the site-specific trends as well as the regional average. The rationale for looking at the regional average is that a GHG signal should cover a wide area.	
62	2	same argument as above We summarize the site-specific trends as well as the regional average. The rationale for looking at the regional average is that a GHG signal should cover a wide area.	
63	box	again the issue here is that we are talking about events that are happening in a short-time and over a small region. Averaging over time and space and develop statistics is probably not appropriate when we are talking about events such as the recent flooding event in Texas. If you average that event over 30 days, it will seem unremarkable. Extreme event totals are 1-day to 5-day,s depending on section discussed. The point being made in the Box is that if you use a too-short record you may underestimate natural variability. I'm not sure how the reviewer's comment challenges this.	
64	1	As noted in NCA5 and shown in the analysis presented in figure 6.4.4 there is a clear trend of increase in extreme precipitation in 12 of the 27 stations analyzed. Again averaging over the entire region is not the best method for picking extreme precipitation events that are local both in time and space. We summarize the site-specific trends as well as the regional average. The rationale for looking at the regional average is that a GHG signal should cover a wide area. Also in this case we point out that the NE behaves differently than other regions.	

69	2	However, there is evidence that flash droughts, which last weeks have increased over the Northeast and Midwest [28] The paper referenced by Reviewer 1 begins with data so recent (1999) that it cannot provide evidence for long-term changes in drought as evidenced in the US Drought Monitor (DM) even though it suggests an increase in "flash droughts" over that period. Keep in mind, the DM is a product of subjective interpretation and objective measures - objective measures that have changed considerably during the past 25 years – thus is not metrically consistent. (One of the CWG authors was an official contributor to the DM for 15 years.) One would wonder what would the 1920's. 30's and early 50's reveal if the DM was operational back then? A more consistent metric is provided in CWG Fig. 6.7.1.	[28]Ronald D. Leeper, Rocky Bilotta, Bryan Petersen, Crystal J. Stiles, Richard Heim, Brian Fuchs, Olivier P. Prat, Michael Palecki, Steve Ansari
70	2	More recent analysis indicate forest loss due to wildfire accelerating over the recent past[29]. In particular there has been an increase in extreme fire radiative power with a 2 fold increase from 2003 to 2023 (period of satellite data availability)[30][31]. However, that these fires are not out-of-sample and there is a fire deficit as shown in figure 6.8.2 should be acknowledged. But this doesn't alleviate the concern that wildfire is leading to lot of socio-economic concerns and needs to be addressed[32] New sentence added: However there is evidence that the intensity of fires in some regions is worsening (Cunningham et al. 2024) and that wildfires resulted in a net loss of global forest cover over 2001-2019 (Tyukavina et al. 2022).	[29]Tyukavina Alexandra , Potapov Peter , Hansen Matthew C. , Pickens Amy H. , Stehman Stephen V. , Turubanova Svetlana , Parker Diana , Zalles Viviana , Lima André , Kommareddy Indrani , Song Xiao-Peng , Wang Lei , Harris Nancy; Global Trends of Forest Loss Due to Fire From 2001 to 2019, Frontiers in Remote Sensing.Volume 3 – 2022,2022. [30]Cunningham, C.X., Williamson, G.J. & Bowman, D.M.J.S. Increasing frequency and intensity of the most extreme wildfires on Earth. Nat Ecol Evol 8, 1420–1425 (2024). https://doi.org/10.1038/s41559-024-02452-2 [31]Patrick H. Freeborn, W. Matt Jolly, Mark A. Cochrane, Gareth Roberts, Large wildfire driven increases in nighttime fire activity observed across CONUS from 2003–2020, Remote Sensing of Environment, Volume 268, 2022,12777 [32]Parks, S.A., Guiterman, C.H., Margolis, E.Q. et al. A fire deficit persists across diverse North American forests despite recent increases in area burned. Nat Commun 16, 1493 (2025). https://doi.org/10.1038/s41467-025-56333-8
71	3	The question of forest management and its role on wildfire frequency and intensity is interesting and deserves further study. We agree	
80	1	The global mean sea-level was increasing at a rate of 0.08 inches/yr in 1993 compared 0.18 inches/yr in 2023, almost double the rate[33], which is approximately what is needed to meet the NOAA projections by mid-century and seems plausible. We don't judge it to be implausibl	[33]Hamlington, B.D., Bellas-Manley, A., Willis, J.K. et al. The rate of global sea level rise doubled during the past three decades. Commun Earth Environ 5, 601 (2024). https://doi.org/10.1038/s43247-024-01761-5

88	3	A possible reason the method used by IPCC (optimal fingerprinting) can be considered to address McKitnick criticism is in [34] We have added citation Chen et al. They mostly just reiterate my points. They propose a resolution to one part of the problem but it requires very restrictive assumptions.	[34]Chen, H., Chen, S.X. & Mu, M. A statistical review on the optimal fingerprinting approach in climate change studies. <i>Clim Dyn</i> 62, 1439–1446 (2024). https://doi.org/10.1007/s00382-023-06975-5
92	4	The role of clouds remains the single most uncertainty in climate modeling, I am glad this was acknowledged here. Agreed	
93	3	The substance of this paragraph was addressed in my comments in earlier sections. Some of the claims made here are either exaggerations of the usual practice (RCP8.5 being referred to as BAU) or the comment about not fit for purpose (a comment extracted from a publication that is calling out for cloud resolved models. Presumably the reviewer agrees RCP8.5 should not be used as a BAU scenario, so we are in agreement. The Palmer and Stevens paper nonetheless says the models are not currently fit for purpose.	
105	2,3, 4,5	The problem with both the FACE studies and the soybean. Maize and wheat studies cited here are that they don't consider the effect of increase in temperature, changes in precipitation, humidity and other environmental factors along with CO2 increases. These compound effects have been shown in wide number of studies [35] [36][37][38][39]. A meta analysis of the compound effects shows that increase in CO2, along with temperature, precipitation changes effects the quality of the cereal and yields[40]. Another recent study evaluated the impacts on C3 and C4 crops and conclude that CO2 enrichment for C3 crops could increase but will be compensated by temperature increase. CO2 fertilization effect was found to be small for C4 [41]. It is important therefore that we consider the compound effects on crop yields and not just focus on CO2 enrichment. The reviewer is correct that compound effects need to be considered, and indeed one of the problems with a lot of econometric papers on climate change and agriculture is they only look at heat and ignore the CO2 enrichment (Taylor and Schlenker being an important exception). Since our remit was impacts of CO2 emissions a brief discussion of FACE plot experiments and other CO2-only experiments is on topic. We discuss meta-analysis of multivariate (compound) experiments in Section 9.3.	[35] Ruiz-Vera UM, Siebers M, Gray SB, Drag DW, Rosenthal DM, Kimball BA, Ort DR, Bernacchi CJ. Global warming can negate the expected CO2 stimulation in photosynthesis and productivity for soybean grown in the Midwestern United States. <i>Plant Physiol.</i> 2013 May;162(1):410-23 [36] Levine LH, Richards JT, Wheeler RM. Super-elevated CO2 interferes with stomatal response to ABA and night closure in soybean (<i>Glycine max</i>). <i>J Plant Physiol.</i> 2009 Jun 1;166(9):903-13. [37]Večeřová K, Oravec M, Puranik S, Findurová H, Veselá B, Opoku E, Ofori-Amanfo KK, Klem K, Urban O, Sahu PP. Single and interactive effects of variables associated with climate change on wheat metabolome. <i>Front Plant Sci.</i> 2022 Oct 10;13:1002561. [38]Thomas, J.M.G., Boote, K.J., Allen, L.H., Gallo-Meagher, M. and Davis, J.M. (2003), Elevated Temperature and Carbon Dioxide Effects on Soybean Seed Composition and Transcript Abundance. <i>Crop Sci.</i> , 43: 1548-1557. https://doi.org/10.2135/cropsci2003.1548 [39] Lesk, C., Anderson, W., Rigden, A. et al. Compound heat and moisture extreme impacts on global crop yields under climate change. <i>Nat Rev Earth Environ</i> 3, 872–889 (2022). https://doi.org/10.1038/s43017-022-00368-8 [40] Ben Mariem S, Soba D, Zhou B, Loladze I, Morales F, Aranjuelo I. Climate Change, Crop Yields, and Grain Quality of C3 Cereals: A Meta-Analysis of [CO2], Temperature, and Drought Effects. <i>Plants.</i> 2021; 10(6):1052. https://doi.org/10.3390/plants10061052 [41]Rezaei, E.E., Webber, H., Asseng, S. et al. Climate change impacts on crop yields. <i>Nat Rev Earth Environ</i> 4, 831–846 (2023). https://doi.org/10.1038/s43017-023-00491-0

106	1	Taylor and Schlenker 2021 also note that 'Climate change will likely have negative impact on agriculture in aggregate, especially in regions exposed to extreme heat. And the CO2-driven yield increases may be offset by effects on food nutrition and quality'. However, the results for US have been a net positive in the recent past but not true in the lower latitudes. Extreme heat may be a net negative, but thus far the overall effects have been positive. Regarding nutrition loss see Section 9.4	
111	1,2	The criticism of NOAA Billion dollar map is likely warranted as it was never completely transparent how the data was generated. However, changing the baseline assumption and refactoring the data using a different set of criteria to make the effects smaller also doesn't make sense. We should continue collecting this data and make the data accessible for researchers and peer review. Figure 10.1 doesn't address these issues, it is another methodology with unknown provenance of the data. We agree that data collection, dissemination and transparency are key. Fig 10.1 is traceable as an indicator though we don't regard it as the final word on the subject either. •	
117	3	Climate change can be expected to increase cold weather extremes in regions that have not been exposed to these effects Not sure what the reviewer's point is.	
118	3	The same Nobel prize winning model in its most recent study concludes that [42] "We conclude with three results relevant for climate policy. First, both current policies (base run) and the extended Paris Accord fall short of limiting global warming to 2 °C or to the cost-benefit optimal level. Second, the economic stakes in global climate policy are substantial, with estimated net present value of economic benefits around \$120 trillion from the cost-benefit optimal policy. Third, once differences in discounting are considered, the baseline DICE-2023 estimate of the social cost of carbon (\$66/tCO₂ for 2020) aligns closely with other recent estimates". Obviously this is the latest and the current version of the model and these results are quite different from thus discussed on this page. These conclusions should also be included in this discussion to avoid selective reading of the literature. We discuss Barrage and Nordhaus (2024) on p. 121.	[42]L. Barrage, & W. Nordhaus, Policies, projections, and the social cost of carbon: Results from the DICE-2023 model, Proc. Natl. Acad. Sci. U.S.A. 121 (13) e2312030121, https://doi.org/10.1073/pnas.2312030121 (2024).

120	1	Similar empirical studies [43] point to "Using an empirical approach that provides a robust lower bound on the persistence of impacts on economic growth, we find that the world economy is committed to an income reduction of 19% within the next 26 years independent of future emission choices (relative to a baseline without climate impacts, likely range of 11–29% accounting for physical climate and empirical uncertainty). These damages already outweigh the mitigation costs required to limit global warming to 2 °C by sixfold over this near-term time frame and thereafter diverge strongly dependent on emission choices. Committed damages arise predominantly through changes in average temperature, but accounting for further climatic components raises estimates by approximately 50% and leads to stronger regional heterogeneity. Committed losses are projected for all regions except those at very high latitudes, at which reductions in temperature variability bring benefits. The largest losses are committed at lower latitudes in regions with lower cumulative historical emissions and lower present-day income". This study uses more of the daily temperature precipitation from 1600 hundred locations world wide instead of global means. There are numerous studies that show the cost, many described in the COP 21 and follow-on meetings The Kotz et al. paper is subject to a cautionary notice at the Nature website that “the reliability of data and methodology presented in this manuscript is currently in question.” https://www.nature.com/articles/s41586-024-07219-0 The literature showing growth effects of temperature increase is pretty robust. And though we don’t cite it, there is a new paper just accepted at Climate Change Economics by McKittrick and Devina Lakhtakia adding to the evidence using 2 newly-constructed global data bases.	[43] Kotz, M., Levermann, A. & Wenz, L. The economic commitment of climate change. <i>Nature</i> 628, 551–557 (2024). https://doi.org/10.1038/s41586-024-07219-0
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Page	para	Comment or Suggested Edit
		The report indicates numerous examples of uncertainties in climate science. It would be extremely helpful if these uncertainties were made more explicit, listed in a concluding section, and prioritized in some way - what are the top 10 priority research areas? If the opening remarks by Secretary Wright and the title pointed to uncertainties and the need for more research, I believe this report will be better received. As I read the report and left review comments below, I bolded items where I gather the authors imply that research is needed. Consider including these kinds of statements throughout and adding a summary. An interesting suggestion but with the time constraints I suggest this be deferred to a separate report.
viii	3	This would be more correct: "Some scenarios of future CO2 emissions overestimate observed levels" Sentence has been removed
viii	5	This would be more correct: Some detailed climate models run "hot" in their simulation of the climate of the past few decades, while many have underestimated the amount of surface warming. More research is needed to select the most skillful and reliable models. The need for more research on model development is implicit. Again, this would be a good topic for a separate report.
viii	6	Need reference for: "Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data." More research is needed to identify how frequency and intensity of weather events are affected by environmental conditions. The ES statements are all supported by the document chapters but suggest we add references to specific sections.
4ff		It is misleading to separate the photo-chemical effects of CO2 from the temperature effects. Extreme heat is hard on plants, causing them to lose water, close stomata, etc. It depends on the plant and the degree of heat. More research is needed to understand how the temperature (mean and variability) affects plant productivity and resilience. 1st paragraph of Section 2.1, Added sentence "Here we focus just on CO₂ fertilization; research on combined effects due to temperature and precipitation changes are discussed in Chapter 10."
7		Again it is misleading to separate the CO2 and the temperature effects on the oceans. The warming surface waters is having significant impact on ocean fish and habitats due to the overall increase in global temperatures This section is specifically on changing alkalinity. We haven't included a review of temperature effects on fish populations: it is one of the impacts topics we were not able to survey.
14	4	More accurate to say "because their effect remain largely unknown". Good examples include natural aerosols (sea salt, dust, biogenic aerosols). Are there others to mention? More research is needed to understand radiative effects of both natural and anthropogenic sources of radiative variability throughout the atmospheric column. Sentence added: "Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because their effects remain largely unknown."
17	figure	What scenarios are the models using in this figure? SRES, as stated in text, also others including Hansen A,B,C and others as described in the Hausfather et al. paper.
19		Vegetation is only one way that CO2 is accommodated by land processes, the other is through soils and microbial processes Microbial dynamics is complex and challenging to understand but may also be a way to boost CO2 absorption by soils (which also enriches the soil nutrients!). More research is needed to better understand how plants and soil systems remove CO2 from the atmosphere.

		Noted.
19	5	More research is needed to improve the understanding and representation of land systems, carbon and nutrient fluxes in models. Noted.
20		Carbon uptake by oceans and ocean ecosystems is less well studied and modeled. The lack of spread of carbon in ocean models may result from insufficient information, ocean biogeochemistry, ecosystems and model development. More research is needed to study and model carbon, nutrient and ecosystem processes and dynamics in ocean models. Noted.
		More research is needed to map warming trends in urban, non-urban and other environments and to ensure accurate representation of regional and global trends in temperature. Noted.
27	2	"This practice" - need to clarify whether this refers to "emergent property" or discarding. I believe the authors mean the latter, but it should be made more clear Sentence rewritten: "Parameter tuning to yield an ECS target was commonplace for the models used in AR4; modelers have moved away from this practice with time."
27	3	"assumed positive cloud feedback" - this is an emergent property too, based on simulation/observation. Should be rephrased to not use the word "assumed". Further research is needed to better understand and model how clouds change with temperature and what the feedback effects are on the radiative balance. Need to clarify if cloud feedbacks are assumed, imposed or both? Can be handled editorially by deciding whether to delete "assumed" or not; deleting it allows it to remain as an implicit modifier.
		Further research is needed to narrow the uncertainty on climate sensitivity, both using models and observations. Noted.
33		The text and figure refer to 33 models, which would include the best and worst. How much does the uncertainty/range change for a subset of best-performing models? The modeling community doesn't have a leaderboard of best-to-worst models. Some of the "prestige" models from the US and UK have very high sensitivities, but they are preferred by many users for particular applications.
34	figure	How many models are included in each case? High ECS 14, Medium ECS 11, Low ECS 13. Added to Figure caption.
36	figure 5.4	How are the lower and mid-troposphere defined? Standard definitions in the paper: LT surface to ~9km, MT surface to ~15 km. Added in the Fig caption.
37	4	"excess amplification" - amplification of what? And Figure 5.6 shows tropics, is this bias only tropical? Sentence changed: "Another important model-observational discrepancy is the excess amplification or warming with altitude..." The bias is only observed in the tropics but the amplification pattern is only predicted in the tropics. Also bear in mind the tropics is nearly half the atmosphere and is where most solar energy enters the climate system.

38		Further research is needed to improve how models represent clouds and dynamics; additional observations are also needed to improve these representations. Noted.
42		Further research is needed to improve how models represent planetary albedo to align with observations. Noted.
		The greater concern with hurricanes is the amount of moisture they carry and drop after landfall, i.e. flooding. While this is an active area of research, it is worth noting that this may be the bigger issue for hurricane change with warming This is covered in the AR6 assessment as quoted, as it's one of the intensity metrics. Currently too little data to assess for trends.
56-57		The concern for many are the extreme hot temperatures without night-time cooling that provides an opportunity for recovery. This section doesn't address this. In this regards, the focus on the difference between extreme hot and extreme cold is misleading when generalizing about decrease in extremes (figure 6.3.4) - the decrease is because we don't have as much extreme cold. This metric is covered by the data in Sct 6.3.3.
60		Combining heat and humidity as a measure of extreme heat is not unusual since it is this combination that is most impactful to human health - the body cannot cool if the humidity and heat are both high. Since a warmer atmosphere holds more moisture, and CO2 causes heat (and therefore moisture) to increase, this combination is a relevant assessment of the effects of CO2 on extreme conditions that make it difficult for people. Also combining with urban regions is helpful since that is where most people live. These points are not made in the report and are important. <u>Sentence</u> be changed to read: "Given the heatwave definition and urban focus, while these increasing values since 1960 point to a growing human impact they are not informative about long term trends or..." Added sentence at end of paragraph (Irrespective of the ultimate cause of regional trends, heatwaves have important effects on society which must be addressed, as we discuss in Chapter 10.) this should address reviewer concerns.
		Patterns and variability of precipitation are poorly understood and models are particularly challenged to represent and predict precipitation, further research in this area is needed Noted.
		The authors rightly describe the extreme uncertainty regarding sea level rise. It would be helpful to add some information about the complex, highly nonlinear and uncertain processes involved with ice-sheet dynamics and ice-sheet - ocean interactions that are especially key for Antarctica. More research is needed to study and model ice sheet dynamics and ice-sheet ocean interactions. Noted. Canvassing ice sheet and ocean dynamics in that much detail beyond our scope but would belong in a separate report.
84	3	Further research is needed on climate variability, effects of ocean circulation, solar variability, model simulation of variability and statistical methods. Noted.
87-88		Anthropogenic aerosol effects may also influence the inflections in temperature in ways that are challenging to account for Noted.
91	2 and 3	Reductions in aerosol indirect (cloud brightening) effects may also explain the reduced planetary albedo, not just from ships but from reduced fossil fuel aerosols coming from the continents, China and east asia especially. This paper describes the reduction in aerosols https://www.nature.com/articles/s41612-023-00488-y This is another area that needs further research! Noted.

94	table 8.1	What are the numbers in the 3rd column? Please include in the caption. Good point. Added to caption: “Numbers refer to footnotes in original source that specify locations or region-specific confidence levels.”
95	2	I don't see an inconsistency between what Ch 11 and Ch 8 say. The first is about precipitation, droughts, tropical cyclones, heat - overall. The 2nd (ch 8) is about specific types of events in specific regions. Suggest to soften the statement about the contrasting assertions. Sentences at issue are “Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes” versus “No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones”. It seems apparent to me that these statements are in conflict.
		The science of attribution of extreme events is challenging and computationally expensive; this is an area where further research is needed with potential to use AI to improve statistics Noted. Not sure about the computationally intensive point: many just run univariate GEV models and overinterpret the results. AI won't fix the bad methodology.
104		This section seems to gloss over many key points. Certainly there are limits where extreme heat and drought (water is key) could be detrimental to crops. It also depends on which crops. There is extensive literature on how certain crop viability is shifting. So a region with particular crop experience and cultivation may no longer be able to sustain that agriculture. There is cost to shifting crops across regions and farmers that needs to be accounted for. And water is key - is there enough water in various regions for energy (power plants need water) as well as agriculture when conditions are very hot for sustained periods? The comment seems to be about the validity of the underlying literature rather than our summary of it. The econometric lit tries to synthesize patterns over large areas to get at overall trends, rather than the agronomy focus on specific sites and crops.
111		Severe weather continues to disproportionately impact lower income communities as well as business that requires outdoor exposure. A thorough analysis would need to include these points and I recommend adding this caveat to the section. This is specifically addressed in Section 10.3.2
		Related to my previous comment, deaths due to extreme heat conditions appear to be increasing, particularly for certain populations and for those with underlying health conditions (which can be hard to detangle when attributing mortality). For example https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2792389 Again this topic is specifically addressed in Section 10.3.2
114		An additional concern is if the grid fails under either extreme heat demands or cold/severe-storm events, the impact on communities will not be uniform and depends on grid infrastructure which can be better in more affluent communities Good point. We don't discuss what makes for grid stability versus instability, especially in the context of many jurisdictions closing reliable power plants and opting for intermittent renewables, but the correlation between extreme weather and the likelihood of power failure is an important topic.
		The impacts of sea level rise and coastal inundation on coastal communities and in low-lying countries should be addressed. This will have impacts particularly on certain countries/regions but also on world economics Good point. The topic is germane but runs into the limits of what we can cover in our limited time. To some extent it is covered in the economics chapter since IAM damage functions include effects of sea level rise on coastal areas.
		Research is needed to better understood the likelihood and impacts of various tipping points, including changes to ocean circulation patterns, ice sheet acceleration, sea-ice loss, die-off of tropical forests, thawing of permafrost, etc. Noted. Hopefully our discussion clarifies the different types of “tipping point” topics.

		Do the authors think it worthwhile for private or public research, such as at DOE, to seek breakthrough technology that might effectively remove massive amounts of CO2 from the atmosphere? No comment
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Chapter Number	Page Number	Approximate Paragraph Number	Comment or Suggested Edit
	i		In general, criticism and re-analysis of past research is always welcome. This report summarizes some substantial concerns from a small group of researchers. The report should be reframed to reflect this and I provide some suggestions in a later comment. I suspect that simply publishing this report will not offset the hundreds of reports and publications on CO2 and Climate that have come before it. But, new analyses and communication within and outside the research community could make a positive difference, should the findings in this report be substantiated. The DOE Office of Science BER could be provided an opportunity to address the research uncertainties in this document in a thorough and robust manner. Noted.
	iii	1	As someone who used to read the DOE reports on CO2 as a graduate student in the 1990s and then conducted numerous analyses of carbon on many topic areas which were later confirmed by numerous other analyses, it seems somewhat cavalier for DOE to issue one brief conclusive report on the "impacts of carbon dioxide emissions". I suggest the following option: Change the title to "Topics of Uncertainty on the Impacts of Carbon Dioxide Emissions on the U.S. Climate" or " An Assessment of CO2 Impacts on Climate to Guide Future Research ", and then use this report to drive research/analyses for each report chapter which would conclude in separate topical reports that could be finished within a year or two. In doing so, the DOE would positively contribute to addressing some of these standing issues and hopefully enable the nation to move forward in a more productive manner. Noted. New title: "A Critical Assessment of the Impacts of Carbon Dioxide Emissions on U.S. Climate."
	vii	Forward	I appreciate the perspective. It could be useful to add or edit the Secretary's Forward to indicate that "the report has been purposefully commissioned to researchers with alternative perspectives in an effort to address these perspectives and provide some closure for the American public, the US Economy, and US energy policy." I suggest this, because it will be very obvious that a handful of skeptics were chosen out of literally hundreds of extremely active and well-respected scientist. Addressing that upfront will immediately reduce criticism, and hopefully generate a positive environment to address these issues. Everyone would like to see convergence of findings on these issues. Noted. The suggested sentence is not well-phrased, but the reviewer is correct that everyone will see the names and know that the document is coming from a particular perspective. The problem is no such concerns were expressed when people with known biases got put in charge of NCA or IPCC chapters. The path to convergence starts with the wider community admitting that they've been keeping a lid on the necessary discussions. We do not have any control over the Secretary's Foreword
	viii	2	Any increase in greening from additional CO2 will likely be more than offset by longer growing seasons with higher temperatures (i.e., more days over 100). This causes serious risk to the US midwestern "bread basket", which is why this has been considered a national security concern. The data supporting this trend has been published a few times now in Science by a fellow out of Stanford, among others. Sources: Lobell and Field. 2007, doi: 10.1088/1748-9326/2/1/014002; also Sloat et al. 2020, doi:10.1038/s41467-020-15076-4 has a thorough introduction with many citations. The effects, including compound effects, on Agriculture are addressed in Ch 9

	viii	3	My understanding is that the upper bound of emissions (i.e., very high) is business as usual, with no mitigation, and a high-end of growth. It's a worst, yet plausible, case scenario. Similarly, the lowest emissions (i.e., very low) scenario includes technologies that don't yet exist including significant CO2 removal. Both are there to understand plausible extremes. The more likely scenarios are the low to high scenarios. I'm sure researchers are open to revisiting how things are bounded and presented if there are reasonable objections. It seems that within the expert community people are quick to set RCP8.5 aside as a fringe scenario. The problem is it dominates the impacts literature and the media coverage thereof. So the critical discussion herein is needed.
	viii	4	This may be true. But data driven analyses may not capture anticipated feedbacks. They attempt to by design. Limited by data especially ocean heat content, but they take it into account.
	viii	6	I am a big fan of data and meta-analysis. However, I'll note that I do not think forest management practices are overlooked. In fact, it is one of the main driving story lines (i.e., too much fuelwood exists, so we need to harvest more forest). There remains strong debate on the efficacy of fuelwood removal over large areas as an effective means of wildfire reduction. The key to this analysis is to look at whether the extent (not the numbers) of fires has grown and whether the burned areas are returning to forests or returning to brush or grassland. If it's the latter, then that is more likely due to regional changes in climate (temp and precipitation). Again the issue may be what experts discuss among themselves versus what's out there publicly.
	viii	8	I think we can point to sea-level rise in south florida, crop damage, and disease vectors fairly easily. I'm not aware of what costs are associated with these 3 items, but I suspect it's quite large. Dealt with in Ch 11 on economic costs and the SCC.
	viii	9	Yes, this is an important paragraph. Most scientists are not activists. Just because there is a science finding, scientists don't expect that to turn into policy. The public and the democratic system can determine the policy using an evidence-based risk/benefit analysis, just as noted here. Opening up this conversation (which should have been done decades ago) would be welcome and would better engage the public on this issue. DOE could in fact take a leading role here and help address a major national issue. A point of sincere agreement.
1	2		This is all generally correct. I would like to think this is common knowledge. Yes but bears repetition
2	4	1	Why use studies based on satellite sensors? I'm quite sure there are studies (again, out of Stanford) that use historic yield data (county-scale USDA data and global FAO data) with associated temperature and precipitation data. Those analyses do not agree with your findings here, I think. But, we can certainly pose these questions to our scientists that study and develop land models and develop a report based on all available data. I'll also note that for sometime data synthesis wasn't considered fundamental science and was therefore largely ignored. Enabling the researchers to conduct robust data analyses on this and other topics would be largely welcomed. See Ch 9 on Ag effects for the studies on yield data.
2	5	Figure 2.2	All data is interesting and useful for perspective and understanding. But isn't the main question whether we are driving up CO2 and temp at a rapid pace in the post-industrial era? This graph does not help answer that question. Figure 2.2 has been deleted.

2	7	3	Stating that increased aridity in drylands will not lead to decreased productivity seems a bit questionable. We can point to precipitation gradients from high to low precipitation that supports forests to grasslands to shrublands, respectively. Less water in general will mean less productivity; this can be seen in different forest compositions as well. The authors cite Zhang et al. (2014), but Zhang's main point is that the direct CO2 effect may be causing greening in drylands that offsets the decreased precipitation. This may be more specific to dryland vegetation, and Zhang et al. specifically state that this finding is relevant to north-east Brazil, Namibia, western Sahel, Horn of Africa, and central Asia. Zhang 2024, not 2014. The point here is to explain benefits of higher CO2 in terms of crop water productivity. Zhang acknowledges increase in desertification (as we note) but points to a global pattern of greening in arid areas.
2	9	3	I do not disagree with this observation of a decline effect, and I have seen it in some of the early biomass energy analyses that appeared in prominent journals and were then corrected over a few years. While it is unfortunate that some try to grab headlines with unsupported assumptions, it does seem that other researchers tend to provide counter arguments and analyses fairly quickly, indicating that the system does in fact work fairly well. Yes, part of the problem is the later counter-evidence gets relatively little attention, hence this report.
3	19	last	Yes, CO2 uptake by land processes have uncertainty associated with them. It's worth noting that DOE researchers (many of whom are retired now) were world-leading and making progress in this area, but nearly all work on CO2 uptake and emissions stopped 10-15 years ago due to political pressure and political concerns. The Carbon Dioxide Information and Analysis Center at ORNL, now cancelled, was a main contributor to the Global Carbon Project. Now the US is woefully behind and ceding expertise on this to the Europeans (as cited in this report). We are also ceding expertise on carbon monitoring via satellites to other countries. There's nothing necessarily wrong with this if this is where the US wants to go, but it's important to recognize that we have lost significant capacity due to policy changes over many years. We specifically recommend the government increase its focus on basic climate monitoring and data dissemination. The CDIAC was very valuable and we lament its closure.
5	44	1	Some of the early work on this topic was done by researchers at Stanford. But there are plenty of other papers. Here's one that came up in a quick search: https://www.pnas.org/doi/10.1073/pnas.0906865106 We discuss this paper in Ch 9.
5	44	1	Contradicting a number of large meta-analyses on the topic of decreased yields with increased temperature is ok. That's what science is all about. But it's going to have to be done in a more robust way than a couple paragraphs here with one or two citations. This section concerns temperature trends in the corn belt; the discussion of yields is in Ch 9.
6	47	chapter summary	This is very important. I have not dug into the data on extreme storm data (both numbers and intensity). Getting researchers together that disagree on a topic, analyze the data, and publish findings together can be very productive. DOE could sponsor a workshop and bring together a broad range of experts and find answers to extreme weather trends. Good idea

6	47	chapter summary	I conducted some analyses on wildfire years ago. I saw the bias in the university textbooks and in the wildfire working groups, who essentially went by textbook teachings. It was rare that people went back to the original data. The last time I checked the actual data (a good 10 years ago), I found that...you're correct...the number of fires had not changed much. What does seem to be changing is that the extent of fires has grown, and this is mostly attributable to hotter and drier conditions. I do not believe there is more fuel load now than there was before the US was settled. Arguing that harvesting will decrease fire is nonsensical; you have no idea where the lightning is going to strike and subsidizing the thinning of all forest in the western fire zone would be cost prohibitive. I think we need to stop using wildfire management as a justification for harvesting. If we want to harvest more, than do it, and stop using fuel load arguments (which is more of a concept than proven reality) as a reason to do it. The biggest issue here is encroachment of housing communities into the Wild-Urban Interface (WUI) and how we want to handle that with policies. Fire is really only bad if it's burning someone's house down. Otherwise, it's a natural progression in forest dynamics. Sources: Campbell et al. 2012. doi:10.1890/110057.; Schoennagel and Nelson. 2011. doi:10.1890/090199. Excellent comments. It's a big topic we can only glance at but we are trying just to get some pertinent data into the discussion.
6	57	6.3.2	The NCA5 is cited here and elsewhere. However, the USGCRP website that hosts the NCA reports has been removed. Hence, there is no way to read and review the referenced findings. This DOE report is therefore arguing against something that no longer exists, and that may appear questionable. Noted. Out of our control.
7	74	2	Given the satellite observed ice sheet dynamics, I'm not sure that ice sheet retreat is that hypothetical. Our reference is to hypothetical instabilities, i.e. massive disintegration.
7	all		This is the first time I have seen all sea-level rise estimates discredited by an offset from land subsidence. This is certainly a global dynamic that we would want to capture and understand in Earth system models, and DOE can look into this further with analyses and experiments if necessary. Noted.
8	86	all	This and other chapters cite the IPCC AR6. The IPCC provides a global process to address the issues and uncertainties in this report. Perhaps this report can set a path for pivoting research and re-engaging in a useful manner. That's a big ask.
9	104	chapter summary	The last sentence in this summary is not necessarily accurate. The authors cite Ainsworth and Long (2020) with respect to increased CO2 effects on crops. But, Ainsworth and Long (2020) indicate that increased temp and decreased precipitation will have negative impacts on crops, while increased CO2 may offset some of those negative effects. It is the impact of CO2 on climate and the subsequent impact on crops that is the concern; not the direct effect of CO2 on crops. Re written: "U.S. agriculture appears to be robust to current and expected CO2-induced warming."

Chapter Number	Page Number	Approximate Paragraph Number	Comment or Suggested Edit
2	3	2.1.1, para. 2	Zheng not in reference list. Do you mean Zeng? Yes, fixed.
2	3	2.1.1, para. 3	"nearly double"? Why exaggerate? - it's a 76% increase. And they reported that future increase in GPP in extra-tropical northern hemisphere (e.g., U.S.) for [CO2] from 300 to 600 ppm of 42%, or 32% more than previous predictions (not 76%). Replace "nearly double" with "much larger than"
2	3	2.1.1, para.1	Zhu also explained that "other factors (OF) not considered in models, such as forest management, grazing, changes in cultivation practices and varieties, irrigation and disturbances such as storms and insect attacks, can be a cause of mismatch between observed and simulated LAI trends.... OF contributes the most to the observed LAI trend over 25.0% (increase) and 5.3% (decrease) of the vegetated area" We don't claim CO2 is the only factor.
2	3	2.1.1, para.2	This report is meant to focus on the U.S., so it would be more appropriate to discuss greening trends in the U.S. Fig. 2.1 shows that the trend in LAI across much of the U.S., with the exception of the Southeast, is less than the global average. Negative OF effects are mainly found in northern high latitudes (e.g., Alaska). Growing season warmth is the dominant factor in cold regions (10.1038/s41558-018-0258-y). Significant browning also is occurring in parts of Alaska (10.1175/EI-D-20-0025.1) But the effect is still positive. In Ch 9 we discuss US-specific evidence concerning CO2 and crop yields.
2	3	2.1.1, para.2	Greening of the Arctic can have important adverse consequences. Direct observations support that warming and increased vegetation cover in the Boreal-Arctic region showed a "robust increasing trend of CH4 emissions (+8.9%) with strong inter-annual variability. The majority of emission increases occurred in early summer (June and July) and were mainly driven by warming (52.3%) and ecosystem productivity (40.7%)." Yuan et al 2024 (10.1038/s41558-024-01933-3). We don't claim it's good or bad, only that it's been observed.
2	3	2.1.1, para.3	Wang et al 2020 (10.1126/science.abb7772) report a decline over recent decades in CO2 effects on global photosynthesis, possibly due to increasing nutrient interactions or interactions with effects on LAI. It's a controversial finding that attracted skeptical comments in <i>Science</i> regarding the validity of the satellite data and the statistical methods used https://www.science.org/doi/10.1126/science.abg2947 https://www.science.org/doi/10.1126/science.abg4420 https://www.science.org/doi/10.1126/science.abg5673 While the authors in reply defend the satellite data, they acknowledge they may not have dealt adequately with confounding non-CO2 factors. So, it seems premature to invoke this result.

2	4	2.1.2	Much of this information in this section is appropriately covered in chapter 9 on agriculture. Chapter 2 purports to have a wider focus (global and environment responses), so it should not dwell on responses of individual crop plants (crops account for only 15% of global GPP). There has been plenty written on ecosystem response to eCO₂, but evidence such as Fig. 2.3 is not relevant. All analyses of direct eCO₂ effects reveal an overriding interaction with other environmental factors (nitrogen and temperature), and global models show that eCO₂ only partially compensates for the negative effects of climate change on ecosystem carbon response. We struggled with how to divide material up in Ch 2 and Ch 9. The solution we came up with was that here we are addressing direct CO₂ effects, namely CO₂ fertilization; later we discuss Ag effects in more detail. Not everyone paid attention in high school biology. Figure 2.3 serves as an illustration of a point that non-specialists are often surprised to learn, namely that CO₂ is plant food.
2	4	2.1.1, last para.	Zhang, 2025 (10.1016/j.ecolind.2025.113762) reported that although vegetation cover was increasing, resilience against external disturbances (drought, heatwaves, wildfires) has simultaneously declined. They use the lag-1 autocorrelation coefficient as the measure of resilience based on Critical Slowing Down theory. The results are suggestive but very noisy and require a lot of assumptions to equate to a loss of ecosystem resilience. Since the authors also show that vegetation cover is increasing at the same time the results don't appear strong enough to merit any change in our discussion.
2	7	2.1.3, para. 2	Cheng did NOT report "increased plant growth"; they reported increased GPP. The distinction is fundamentally important, has been recognized for decades, and is completely ignored in this chapter. Cheng et al. did refer to an increase in Net Primary Production as well, but you are correct they focused on Gross Primary Production. Sentence rephrased "Similarly, Cheng <i>et al.</i> (2017) noted that increased Gross Primary Production from 1982 to 2011 due to rising..." and GPP be added to the Glossary. More generally since GPP and NPP are closely correlated the use of "plant growth" is suitable.
2	6-7	2.1.3	This material is repeated in chapter 9 where it belongs. Here, it would be more appropriate to focus on how eCO₂ interacts with drought on ecosystem response (e.g., 10.3390/atmos12020212) We tried to avoid repetition but there is some. We discuss drought in Ch 8: since we don't see global and US trends, the issue of declining CO₂ fertilization during droughts isn't a key issue at this point.
3	19	3.2.2, last para.	Regarding the uncertainty in the land sink, a primary reason for this uncertainty is that the primary response of photosynthesis to CO₂ does not predict C sequestration because of strong interactions between CO₂ and climate, nutrients, stand dynamics, and other factors. That is why the almost complete focus in this report on crop plants and plant responses in greenhouses does not inform us about "CO₂ uptake by land processes" We aren't making any strong claims about the land sink, we only report the results in the Global Carbon Project. Not sure if the reviewer is challenging them or not.
9	104	all	This chapter is silent on agricultural effects on atmosphere and climate. Sokal and Kachel 2025 (10.3390/en18092272) conclude: "The current study demonstrated that agricultural activities significantly contribute to the emissions of three main greenhouse gases: carbon dioxide, nitrous oxide, and methane." Emissions from the Ag sector are included in the IAM results discussed in Ch 11.

9	105	9.2, para. 2	The section title is "Field studies..." but the next three paragraphs are primarily about responses of potted plants in growth chambers or greenhouses (with exception of Blandino, which was a field study and showed a much smaller response than the pot studies). There is an important reason that the field data cited in Blandino and in SoyFACE show a smaller response than data from the potted plants under artificial conditions. These data are barely relevant to the topic you are trying to address. FACE plot studies are field studies, and we also discuss other field studies. However we also include some lab experiments. <u>Heading changed to "Field and laboratory studies of CO2 enrichment."</u>
9	105	9.2, para. 3, 4, 5	CO2Science.org website is a highly biased and unreliable website. They report on papers, or specific sentences in papers, that support their view and ignore conflicting reports or qualifying sentences. If there was another site that gathered that much data, we'd cite it. We'd need some evidence of actual bias to disqualify the CO2Science.org archive given the extent of its coverage.
9	105	9.2, para. 3	This is a report for the US. Why are you citing soybean studies in China when there is a major soyFACE study in Illinois? Yield in SoyFACE increased in eCO2 but declined with increasing temperature (10.1093/jxb/erac503). eCO2 did not result in water savings as hypothesized but rather increased soil moisture depletion. (10.1098/rstb.2024.0230) The Chinese study is on point regarding CO2 enrichment. The first study referenced by the reviewer (10.1093/jxb/erac503) only subjected soybean to elevated temperature without varying CO2, so it isn't relevant to our discussion. The second reference is to a general literature survey which doesn't appear to say anything different from what our chapter says.
9	106	9.2, para. 2	Ainsworth et al, 2025 (10.1093/jxb/erac503) state: "Early season stimulation in biomass at elevated [CO2] more than offset lower stomatal conductance in crops, resulting in greater depletion of soil moisture, instead of water savings [30,31]. Wheat tiller survival and grain filling was also reduced by elevated [CO2] under dry conditions [32]. The CO2 fertilization effect was also significantly reduced by growth at elevated temperatures in FACE experiments, again suggesting that high atmospheric [CO2] may not offset the negative impacts of global warming [29]. Thus, it may be that, to date, elevated [CO2] and the resultant climate changes have had net positive effects on agroecosystem productivity, but as climate change intensifies, there will be a shift towards net negative effects as has been suggested for natural ecosystems [3]." Our summary statement on the Ainsworth review is accurate regarding the CO2 effect. They raise the question of compound effects from simultaneous changes in CO2 and temperature. That topic is taken up in the discussion of the NBER study and Section 9.3

9	107	1st para.	Another study that should be cited is Hultgren et al, 2025 (10.1038/s41586-025-09085-w). "For all crops except rice, we estimate that warming will likely reduce global yields by 2050 (probability of loss ranges from 0.701 (sorghum) to 0.946 (wheat)... " "We estimate that global production declines 5.5×10^{14} kcal annually per 1 °C global mean surface temperature (GMST) rise (120 kcal per person per day or 4.4% of recommended consumption per 1 °C; $P < 0.001$). We project that adaptation and income growth alleviate 23% of global losses in 2050 and 34% at the end of the century (6% and 12%, respectively; moderate-emissions scenario), but substantial residual losses remain for all staples except rice." Regions with moderate average temperatures tend to suffer the largest yield losses. "Adjusting for CO2 fertilization does not qualitatively alter the structure of our findings ... but it does reduce the central estimate for end-of-century yield losses by 5.0– 9.5 percentage points... and increases the likelihood of positive aggregate effects." The Hultgren study came out after our draft had been complete. The headline results which generated massive publicity were based on RCP8.5 with no CO2 fertilization. One of our other reviewers wondered why we focused so much on the deficiencies of RCP8.5 when everyone knows it's a marginal case – this study is a good illustration of why. Fig 3 in Hultgren
9	108	1st	Reference to Ziska paper greatly mischaracterizes it. Ziska clearly indicates an effect of eCO2 on nutritional quality, but he indicates there is uncertainty in some of the mechanisms behind that response, including the simple dilution hypothesis. He states up front: "However, it is the direct effect of rising [CO2] on plant chemistry and stoichiometry that represents a continuing threat to the nutritional integrity of both human and animal systems." Ziska doesn't dismiss CO2, but he points out that nutrient dilution has also been observed under historical conditions in which CO2 was likely not the driver. Sentence rephrased "as is the evidence that nutrient dilution observed to date is entirely attributable to higher CO₂"
9	108	9.4, para. 1	Evidence for nutritional decline under eCO2 is widespread: Toreti et al, 2020 10.1038/s43016-020-00195-4) "A meta-analysis of 228 pairs of experimental observations on barley, potato, rice and wheat reported reductions in protein concentrations ranging on average from –15.3% to –9.8% under eCO2, while the reduction was relatively small (–1.4%) in soybean." AND Ainsworth et al 2025: "The positive 'CO2 fertilization' effect on crop yield is complicated by a decrease in many nutrients in elevated [CO2]. An analysis of 130 varieties of plants found that elevated [CO2] decreased the concentration of 25 important minerals by 8% on average, and the carbohydrate to mineral ratio was increased in these plants." We don't dispute any of this; it corresponds with what we say.
9	109		URL for Taylor and Schlenker paper is incorrect. It should be https://www.nber.org/papers/w29320. "papers" not "paper. Was this report peer reviewed? I cannot find it in a peer-reviewed journal. Thanks for the correction. I don't think it has appeared in print anywhere other than the NBER series.

12	129	This chapter is highly distressing, but I suppose it encapsulates the whole thesis of the document. Apparently, there is no point in policies to reduce emissions (or make the necessary changes in energy policy to accomplish emission reductions) because it will make no difference to the atmospheric CO2 concentration or climate. So why bother? Would you have said this in 1970 (CO2= 326), 1990 (CO2 = 354 ppm), or 2010 (CO2=390)? Probably so. And in 30 years when CO2 is 500 ppm, will it be fair to look back and evaluate your apparent call for inaction in the statement here "And even if global emissions were to stop tomorrow, it would take decades or centuries to see a meaningful reduction in the global CO2 concentration and hence human influences on the climate." But I suppose this attitude is justified if there is no adverse consequence and the only important effect of rising CO2 is to make little plants in greenhouse grow bigger (e.g., Fig. 2.3), and indirect effects on heat stress, drought, fires, sea level, etc. aren't worth discussing. Points taken but the reviewer is calling attention to actual problems finding mitigation strategies with positive net benefits.
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Ch	Page	para	Comment or Suggested Edit
1	2	full text	This chapter points out that the primary concern around human emissions of CO2 is that it changes the radiative balance of the atmosphere. The chapter also makes the points that CO2 has no toxicological effects on humans at current atmospheric levels, and that CO2 is necessary for photosynthesis, with the potential to stimulate plant growth at higher concentrations. These points are well-established scientific facts. Yes and experts know them but non-experts aren't necessarily aware of them.
2	3	3	It would be more reflective of the literature to say here that "Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO2 levels, changes in climate, changes in nitrogen deposition, land cover change, and other factors." We have added "in part" to sentence.
2	3	3	While the Zhu et al. 2016 study did find that 70.1% (+/- 29.4%) of the integrated global change in LAI was attributable to changes in CO2, most of the observed change in LAI is concentrated in the tropical forest regions of South America, Africa, and Indonesia, as shown in this report's Figure 2.1, reproduced from Zhu et al. In terms of the fraction of global land area influenced most by the factors considered in Zhu et al. 2016, effects on LAI from changing climate is the dominant factor (positive effects for 28.4% of land area plus negative effects on 4.7%, for a total area with dominant climate influence of 33.1%), followed by other factors not represented explicitly in the study or in the models (positive effects on LAI from other factors over 25.0% of land area plus negative effects over 5.3%, for a total area with other factors as the dominant effect of 30.3%), and then CO2 effects (23.2% of land area dominated by positive effects and 0.1% with negative effects, for a total of 23.4%). Since the report is focused on the U.S. it would be helpful to indicate the global context for the numbers reported. We have added new text "Other contributors included land-use changes, warming and nitrogen. The fraction attributable to CO2 was largest in the tropics; other factors played more dominant roles in CONUS."
2	3	3	The dominant factors related to changes in LAI over the U.S. (including Alaska) are land cover change (+LCC), climate effects (+CLI), other factors (+OF and -OF), and then CO2 (+CO2). There are more extensive regions where +CO2 is the dominant factor for the boreal forest zone in Canada. Given that, and given the explicit focus of the report on the U.S., it would be useful to call out in this section that the global greening pattern has distinct geographic variation in driving factors, and that over the target geography of the U.S. it seems to be dominated by factors other than increasing CO2. See my powerpoint slide 1 for a zoom on the area of interest from the Zhu et al. 2016 paper. Addressed with new sentence: CO2 fertilization effects are influenced by local temperature and nutrient and water availability, all of which vary regionally.
2	3	4	"Zheng et al. (2017) confirmed the pattern..." should be modified to say "Zhen et al. (2017) confirmed the pattern of observed greening..." As written, and in the context of the previous paragraph, the current text suggests that Zheng et al. 2017 confirmed the pattern of greening being related mainly to increased CO2, a factor which was not examined in their study. Changed: confirmed the pattern of greening, noting that over thirty years it had added 8 percent...
2	3	4	Without the addition of the appropriate context in the preceeding paragraph (my notes 3, 4, and 5) the remainder of this paragraph could be misinterpreted to mean that the impacts of greening on air temperature are attributable back to a positive effect of CO2 on greening. Rewording has addressed this.

2	3	4	The sentence "Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it through land management changes" is misleading. Chen et al. (2019) shows that China and India are <i>causing</i> the observed greening in large areas by intentionally increasing the land area occupied by forests (China) and increases in harvested area in croplands, mainly due to multi-cropping, heavy fertilizer use, and expanded irrigation (China and India). It would be more accurate to say "Greening has been observed globally, but Chen et al. (2019) represent a disproportionate fraction of the total greening trend, accomplished through intentional increases in forest area (China), and expansion of multi-cropping, fertilizer use, and irrigation in croplands (China and India)." Changed: "Greening has been observed globally. Chen et al. (2019) show that in China and India much of it is driven by land management changes"
2	3	3 and 4	Given the changes suggested in these two paragraphs, it raises the question of whether the section title (CO2 and global greening) is itself misleading. That title wrongly suggests that all the content to follow is reflective of a direct influence of CO2 on the observed global greening trends, when the literature presents a much more <i>nuanced</i> interpretation. The changed to CO2 as a contributor to global greening
2	3	3 and 4	It would be worth noting in this section that the multiple remote sensing-based datasets for LAI changes have remarkable differences, especially when comparing the figure 2.1 reproduced from Zhu et al. 2016 with the MODIS-based data record from Chen et al. 2019 (their figure 1). That means it is difficult to place a lot of confidence in the attribution of changes in different regions to different factors. See my powerpoint slide 2 for a comparison of the four datasets used in Zhu et al. 2016 and Chen et al. 2019. Thank you for this information. It is an interesting point but gets into more specialized detail than is necessary for this report.
2	3	5	The authorship for the Haverd et al. 2020 citation is not correct in the References section for this chapter. The correct citation is: Haverd, V., B. Smith, J. G. Canadell, M. Cuntz, S. Mikaloff-Fletcher, G. Farquhar, W. Woodgate, P. R. Briggs and C. M. Trudinger 2020. Higher than expected CO2 fertilization inferred from leaf to global observations. Global Change Biology 26(4): 2390-2402 DOI: https://doi.org/10.1111/gcb.14950. Corrected
2	3	5	A more recent and more comprehensive study (Keenan et al. 2023) reexamined multiple data constraints and concluded that the model used in Haverd et al. 2020 (CABLE) is outside the likely range of CO2 fertilization effects, with higher CO2 fertilization than indicated by multiple independent constraints. At the very least this more recent paper should be cited in the report, with text indicating that the central estimate from the TRENDY models is more likely to be in the range of observational constraints than is the CABLE result. As it stands the report suggests that the latest science indicates that most models have underestimated the fertilization effect, and the literature doesn't currently support that conclusion. See: Keenan, T. F., X. Luo, B. D. Stocker, M. G. De Kauwe, B. E. Medlyn, I. C. Prentice, N. G. Smith, C. Terrer, H. Wang, Y. Zhang and S. Zhou 2023. A constraint on historic growth in global photosynthesis due to rising CO2. Nature Climate Change 13(12): 1376-1381 DOI: 10.1038/s41558-023-01867-2. Added sentence: However Keenan et al (2023) estimated a lower fertilization rate more in line with models.

2	4	1	The attribution analysis in the Chen et al. 2024 paper is very sensitive to the choice of multiple regression vs. partial correlation (their figures 3 vs S7, respectively), and in both cases they seem to misattribute the significant increases in LAI in India and China to CO2 rather than to changes in landcover and cropping practices. This kind of regression-based attribution is less informative than the model-based inference used for example by Zhu et al. 2016. The description of sensor calibration issues in this paper is also very cursory. It would probably be better to refer to the review paper of Piao et al. 2020 to support the claim of continued greening. Piao, S., X. Wang, T. Park, C. Chen, X. Lian, Y. He, J. W. Bjerke, A. Chen, P. Ciais, H. Tømmervik, R. R. Nemani and R. B. Myneni 2020. Characteristics, drivers and feedbacks of global greening. Nature Reviews Earth & Environment 1(1): 14-27 DOI: 10.1038/s43017-019-0001-x. Thank you for the comment. We have taken out the details about the Chen et al. analysis and say simply “Piao et al. (2020) and Chen et al. (2024) report that the greening trend continues with no evidence of slowdown, and CO2 fertilization remains the dominant driver”
2	4	2	The section 2.1.2 (Photosynthesis and CO2 levels) lacks coherence. It seems to be a collection of uncontroversial points about the ability of increased CO2 concentration to stimulate plant growth and reduce water loss through stomates. Figure 2.2 seems intended to show that the current levels of CO2 are not high compared to levels experienced in Earth's deep geologic past. A balanced treatment of the topic might call out the rate of change in CO2 concentration from human-caused emissions, and how both that rate and the absolute levels diverge radically from rates of change and ranges of variability over the past hundreds, thousands, and hundreds of thousands of years. See my powerpoint slide 3 for an example set of figures that might be included. In response to another reviewer, we have added the sentence “While the modern rate of change in CO2 is likely high compared to all prior intervals, the geological evidence is that plants and animals evolved under much higher CO2 levels than at present.”
2	7	4	The report suggests that the topics of CO2 fertilization and increased water use efficiency are not adequately treated in recent IPCC reports. In IPCC's AR6 WG I report there is an entire chapter devoted to an assessment of carbon cycle processes (Chapter 5, Global Carbon and Other Biogeochemical Cycles and Feedbacks). This is precisely where one would expect to find information about CO2 fertilization and water use efficiency. In the Executive Summary for the chapter is the following bolded headline: Increases in atmospheric CO2 lead to increases in land carbon storage through CO2 fertilization of photosynthesis and increased water use efficiency (high confidence). The associated Executive Summary text includes reference to two figures, three chapter sections, and a cross-chapter box all dealing directly with this topic. The Executive Summary text also references the important topic of nutrient dynamics and their interactions with fertilization and ecosystem-climate feedbacks, a critical nuance of the interaction of CO2 and vegetation productivity that is ignored in the report reviewed here. We acknowledge that the topic is addressed in the body of IPCC reports. But we draw attention to its omission from summary documents.

2	8	2	Section 2.2.2 (Coral reef changes) has a strong focus on past examples of early investigations that are later updated. There is also a note about the difficulty of publishing negative results, with a quote that this pattern "is true across all of science". Given the objective of this report, I suggest a shift in tone away from complaints about the kinds of papers that do and don't receive media attention, and instead highlight the latest synthesis of results about the likely future of coral reefs. A relatively recent synthesis paper (Cornwall et al. 2021) in a well-respected journal (PNAS) based on collated data from 233 locations worldwide projects that 37% of reefs will stop accreting and thus fail to keep up with sea level rise by 2050 under the low emissions RCP2.6 scenario, and no reefs would be able to accrete at a rate to stay ahead of sea level rise by 2100 under either RCP4.5 or RCP8.5. This analysis finds that most of the loss of net accretion rate is due to bleaching events, and a minority of the impacts are due to "direct physiological impacts of ocean warming and acidification on calcification or bioerosion". C.E. Cornwall, S. Comeau, N.A. Kornder, C.T. Perry, R. van Hooidek, T.M. DeCarlo, M.S. Pratchett, K.D. Anderson, N. Browne, R. Carpenter, G. Diaz-Pulido, J.P. D'Olivo, S.S. Doo, J. Figueiredo, S.A.V. Fortunato, E. Kennedy, C.A. Lantz, M.T. McCulloch, M. González-Rivero, [...] & R.J. Lowe, Global declines in coral reef calcium carbonate production under ocean acidification and warming, Proc. Natl. Acad. Sci. U.S.A. 118 (21) e2015265118, https://doi.org/10.1073/pnas.2015265118 (2021). This is a model projection study whereas for the very limited purpose of this section we are focusing on current and historical observations.
3	14	1	The study by Connolly et al. 2021 uses a linear regression approach to estimate the amount of variability in surface temperature trends that could be explained by total solar irradiance time series. Their approach is to first model the temperature trend with TSI as the dependent variable, and then compare the residuals from that fit to anthropogenic forcing factors. This is an obviously biased approach, and in fact a full paper was published the following year (in the same journal) laying out the erroneous methods and the faulty conclusions they produce (Richardson and Benestad 2022). Richardson, M. T. and R. E. Benestad 2022. Erroneous use of Statistics behind Claims of a Major Solar Role in Recent Warming. Research in Astronomy and Astrophysics 22(12): 125008 DOI: 10.1088/1674-4527/ac981c. While I agree with R&B that a partial regression is biased unless the regressors are orthogonal, Connolly et al. replied in 2023 at https://iopscience.iop.org/article/10.1088/1674-4527/acf18e in which they used updated AR6 data and reproduced their main result using multiple regression. However they also emphasized that it is only one of many possible results depending on choice of solar proxy and surface T record,
3	18	1	Section 3.2.2 (The carbon cycle relating emissions and concentrations). There is no new information or analysis presented in the chapter, and it relies heavily on Global Carbon Project information. Figure 3.2.3 is described as showing a seven-fold difference in the recent trend in land carbon sink estimates across land models, and this is given as a potential driver of uncertainty in future carbon cycle and climate change predictions. Variation among models is well known and is one of the reasons exercises like CMIP and GCP rely on multi-model ensembles when assessing the state of the science. The distribution of results looks fairly typical in this diagram, with a strong central value around 1.3 to 1.3. We're not claiming to have added new information, just reviewing what's out there.

12	129	3	The following sentence is misleading: "And even if global emissions were to stop tomorrow, it would take decades or centuries to see a meaningful reduction in the global CO2 concentration and hence human influences on the climate." It is true that bringing global emissions immediately to zero would not reduce CO2 concentrations on short timescales. It is not true that this same scenario means no reduction in human influence on the climate. We must compare the zero emissions scenario to something, and the most meaningful comparison is the current trajectory of increasing emissions and the resulting super-linear increase in concentration. So by reducing emissions to zero we clearly avoid the expected increases in concentration and the expected increases in radiative forcing together with increased near surface air temperature and all the other expected consequences. So our change in action - going to zero emissions - does in fact have an immediate and growing human influence on the trajectory of the climate system. That is not an argument for reducing our emissions to zero tomorrow, it is just an argument for logic and clarity in how we talk about consequences of different actions. The sentence in the text is correct. It's also true to say that going to zero emissions would, over time, open up a widening gap between observed and counterfactual. But realistically we are only looking at marginal changes. The stock-flow mismatch is one reason IAMs have not recommended going to zero emissions.
12	129	5	Regarding the sentence "The practice of referring to unilateral U.S. reductions as "combatting climate change" or "taking action on climate" therefore reflects a profound misunderstanding of the scale of the issue." This makes the dubious assumption that when people refer to "combating climate change" or "taking action on climate" they are ignorant of the scale of the problem. Instead, it is probably more justifiable to assume that it is well-understood by most people who advocate for these local and national changes that the major emitters must act together to make a big difference in global emissions. It is at least worth considering, in the context of this report, that a path toward action at the necessary scale will require local and national action from a broad consortium, and that individual advocacy is a useful and necessary starting point for shifting the inertia of global policies. Sentence modified to read "The practice of referring to unilateral U.S. reductions as "combatting climate change" or "taking action on climate" on the assumption we can stop climate change therefore reflects a profound misunderstanding"